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Electricity Consumption Prediction System Based On Deep Learning.

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In front of the Jury composed of:

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May Allah bless and reward all those who supported us.

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Dedications

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Rihab Amir

Abstract

Electricity consumption forecasting is essential for improving building energy management, reducing operational costs, and detecting unusual consumption behavior. This project presents a deep learning approach for multi-building electricity forecasting and abnormal consumption increase detection using the Building Data Genome Project 2 dataset.

The proposed system uses historical electricity readings, temporal features, weather data, building metadata, lag features, and rolling statistical features to predict future electricity consumption. A Gated Recurrent Unit (GRU) neural network is employed due to its effectiveness in modeling sequential time-series data. Building embeddings are integrated to capture differences between buildings while training a unified forecasting model. The dataset is divided chronologically into training, validation, and testing sets to ensure a realistic forecasting process.

Model performance is evaluated using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and R-squared (R^2). In addition to forecasting, the project implements abnormal consumption detection using rolling baseline analysis and forecast residual analysis. These methods identify sudden increases in electricity usage by comparing actual consumption with historical patterns and model predictions.

The results demonstrate the effectiveness of deep learning for multi-building electricity forecasting and abnormal increase detection, providing a practical framework for intelligent energy monitoring and data-driven energy management.

Keywords: Electricity consumption forecasting, deep learning, GRU network, time series, anomaly detection, building energy management, Building Data Genome Project 2, energy consumption, artificial intelligence, predictive analytics.

Résumé

La prévision de la consommation électrique est essentielle pour améliorer la gestion énergétique des bâtiments, réduire les coûts opérationnels et détecter les comportements de consommation inhabituels. Ce projet présente une approche basée sur l'apprentissage profond pour la prévision de la consommation électrique multi-bâtiments et la détection des augmentations anormales de consommation en utilisant le dataset Building Data Genome Project 2.

Le système proposé utilise les relevés historiques de consommation électrique, les caractéristiques temporelles, les données météorologiques, les métadonnées des bâtiments, ainsi que les variables de retard et les caractéristiques statistiques glissantes afin de prédire la consommation électrique future. Un réseau de neurones de type Gated Recurrent Unit (GRU) est employé grâce à son efficacité dans la modélisation des séries temporelles séquentielles. Des embeddings spécifiques aux bâtiments sont intégrés pour permettre au modèle de capturer les différences entre les bâtiments tout en entraînant un modèle unique partagé. Le dataset est divisé chronologiquement en ensembles d'entraînement, de validation et de test afin de garantir un scénario de prévision réaliste.

Les performances du modèle sont évaluées à l'aide des métriques standards : Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE) et le coefficient de détermination (R^2). En plus de la prévision, le projet met en œuvre une détection des consommations anormales à l'aide de l'analyse par baseline glissante et de l'analyse des résidus de prévision. Ces méthodes permettent d'identifier les augmentations soudaines de consommation électrique en comparant la consommation réelle aux comportements historiques et aux prédictions du modèle.

Les résultats démontrent l'efficacité de l'apprentissage profond pour la prévision de la consommation électrique multi-bâtiments et la détection des augmentations anormales, offrant ainsi un cadre pratique pour la surveillance intelligente de l'énergie et la prise de décision basée sur les données.

Mots-clés : Prévision de la consommation électrique, apprentissage profond, réseau GRU, séries temporelles, détection d'anomalies, gestion énergétique des bâtiments, Building Data Genome Project 2, consommation énergétique, intelligence artificielle, analyse prédictive.

ملخص

يُعد التنبؤ باستهلاك الكهرباء من المهام الأساسية لتحسين إدارة الطاقة في المباني، وتقليل التكاليف التشغيلية والكشف عن سلوكيات الاستهلاك غير الطبيعية .يقدم هذا المشروع مقاربة تعتمد على التعلم العميق للتنبؤ باستهلاك الكهرباء في عدة مبانٍ والكشف عن الزيادات غير الطبيعية في الاستهلاك باستخدام مجموعة بيانات Building Data Genome Project 2.

يعتمد النظام المقترح على قراءات استهلاك الكهرباء التاريخية، والخصائص الزمنية، وبيانات الطقس، وبيانات المباني، بالإضافة إلى خصائص التأخير والخصائص الإحصائية المتحركة، من أجل التنبؤ بالاستهلاك الكهربائي المستقبلي .تم استخدام شبكة عصبية من نوع Gated Recurrent Unit (GRU) نظراً لقدرتها العالية على تمكين النموذج (Embeddings) نمذجة بيانات السلاسل الزمنية المتتابعة .كما تم دمج تمثيلات خاصة بالمباني لتمكين النموذج من تعلم الفروقات بين المباني مع الحفاظ على نموذج موحد للتنبؤ .وتم تقسيم مجموعة البيانات زمنياً إلى مجموعات تدريب وتحقق واختبار لضمان محاكاة واقعية لعملية التنبؤ.

وجذر متوسط ،(MAE) تم تقييم أداء النموذج باستخدام معايير التقييم القياسية، وهي :متوسط الخطأ المطلق بالإضافة إلى التنبؤ، .(R^2) ومعامل التحديد ،(MAPE) ومتوسط نسبة الخطأ المطلق ،(RMSE) مربع الخطأ يقوم المشروع بتنفيذ نظام لاكتشاف الزيادات غير الطبيعية في الاستهلاك باستخدام طريقتين :طريقة خط الأساس المتحرك، وطريقة تحليل بقايا التنبؤ .تساعد هذه الطرق على اكتشاف الارتفاعات المفاجئة في استهلاك الكهرباء من خلال مقارنة الاستهلاك الفعلي بالأنماط التاريخية وتوقعات النموذج.

تُظهر نتائج هذا المشروع فعالية التعلم العميق في التنبؤ باستهلاك الكهرباء لعدة مبانٍ والكشف عن الزيادات غير الطبيعية، مما يوفر إطاراً عملياً للمراقبة الذكية للطاقة ودعم اتخاذ القرارات المبنية على البيانات في إدارة الطاقة.

الكلمات المفتاحية

السلاسل الزمنية، كشف الشذوذ، إدارة طاقة المباني، GRU، التنبؤ باستهلاك الكهرباء، التعلم العميق، شبكة : مجموعة بيانات ، استهلاك الطاقة، الذكاء الاصطناعي، التحليلات التنبؤية.

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Acronyms List

AI : Artificial Intelligence

ANN : Artificial Neural Network

ARIMA : AutoRegressive Integrated Moving Average

ASHRAE : American Society of Heating, Refrigerating and Air-Conditioning Engineers

BDG2 : Building Data Genome Project 2

CDD : Cooling Degree Days

CNN : Convolutional Neural Network

CNN-LSTM : Convolutional Neural Network – Long Short-Term Memory

CNN-TFT : Convolutional Neural Network – Temporal Fusion Transformer

CO_2 : Carbon Dioxide

EPM : Electricity Prediction Model

GRU : Gated Recurrent Unit

HDD : Heating Degree Days

kWh : Kilowatt-hour

LSTM : Long Short-Term Memory

MAE : Mean Absolute Error

MAPE : Mean Absolute Percentage Error

MLP : Multi-Layer Perceptron

MSE : Mean Squared Error

MTLF : Medium-Term Load Forecasting

PV : Photovoltaic

ReLU : Rectified Linear Unit

RMSE : Root Mean Squared Error

RNN : Recurrent Neural Network

R^2 : Coefficient of Determination

Seq2Seq : Sequence-to-Sequence

STLF : Short-Term Load Forecasting

TCN : Temporal Convolutional Network

TFT : Temporal Fusion Transformer

UCI : University of California, Irvine

U-235 : Uranium-235

U-238 : Uranium-238

General Introduction

The rapid growth of urbanization and industrial activities has led to a significant increase in electricity demand, making energy management a critical challenge for modern societies. Inefficient consumption patterns not only strain power generation systems but also lead to energy waste, higher operational costs, and increased environmental impact. In countries such as Algeria, these challenges are further intensified by population growth, seasonal demand fluctuations, and the integration of renewable energy sources, which introduce additional variability into the electrical grid.

Electricity consumption has become a key indicator for planning and decision-making in smart grids, as accurate forecasting is essential to ensure stability, reliability, and efficient resource allocation. However, predicting energy demand is a complex task due to the dynamic and nonlinear nature of consumption behavior, which is influenced by multiple factors such as time, weather conditions, and building usage patterns.

To address these challenges, it is necessary to develop intelligent systems capable of analyzing historical consumption data and providing accurate short-term predictions. Traditional statistical methods may struggle to capture complex temporal dependencies, which has led to the increasing adoption of advanced approaches based on artificial intelligence.

In this context, deep learning techniques, particularly models designed for time series analysis, have demonstrated significant potential in improving prediction accuracy. These models are capable of automatically learning hidden patterns and temporal dependencies within large volumes of data, making them highly suitable for electricity consumption forecasting.

In this thesis, we propose a deep learning-based system for predicting electricity consumption using building-level electricity meter data. The proposed approach focuses on modeling temporal patterns in load curves and aims to provide accurate and reliable forecasts to support smart grid management and energy optimization.

Chapter 1: stat of the art.

Chapter 1: State of the art

1. Introduction:

For decades, electricity consumption has been a fundamental aspect of economic development and daily life, reflecting the growth of urbanization and technological advancement. However, with the increasing complexity of modern energy systems and the rising demand for electricity, consumption patterns have become more dynamic and difficult to manage. As a result, the challenges associated with energy distribution, efficiency, and sustainability have evolved significantly over time.

The objective of this chapter is, firstly, to provide a descriptive analysis of electricity consumption patterns and their temporal behavior, highlighting the main factors that influence demand variations. Secondly, a qualitative analysis of existing approaches proposed by the scientific community for electricity consumption forecasting will be conducted, with the aim of identifying their limitations and suggesting potential improvements, particularly through the use of deep learning techniques.

2. Overview of electricity consumption:

2.1definition of energy:

Energy is an older concept that comes from Latin, from the Greek *enérgia*, which means “force in action.” According to the universal dictionary: “energy is the capacity of a system to modify a state, to produce work resulting in motion, light, or heat.”

Energy can also be defined as a physical quantity that characterizes the state of a system and is globally conserved during the different transformation processes. Moreover, energy can also be classified according to its source.

of extraction and the means by which it is conveyed. Thus, a distinction is made between so-called renewable energies and others that are non-renewable.

“Energy is a physical quantity that exists in different forms (electrical, mechanical, chemical, food). Energy transforms from one form to another, but every conversion is accompanied by a degradation of energy ‘Carnot principle’.” [1]

2.2. Sources and types of energy:

Given the importance of energy and its role in various fields, regardless of its type or the source on which it relies, in the following we will explain the sources and types of energy.

2.2.1. Energy sources:

This section provides details on the origin of energy. The main types of energy we use are fossil fuels such as oil, coal, and gas, which are non-renewable and are therefore used only once. The emissions they produce contribute significantly to global warming. Other types of energy, from renewable sources such as the sun, wind, or water, exist continuously and do not contribute at all to global warming. We can also produce energy from resources that can nowadays be considered as “waste.”

We can therefore obtain energy from many different sources, some of which are more efficient and cleaner than others.

2.2.2. The different types of energy:

We can classify energy according to several criteria, which we will mention below:

2.2.2.1. Renewable energies:

Environmental protection has become a major concern. Many research directions have therefore focused on the use of renewable energies. Any type of energy that can be produced from a natural resource that does not decrease as a result of its use is called “renewable,” as shown in . [2]

An energy source is renewable if consuming it does not limit its future use. This is the case for energy from the sun (solar energy), wind (wind energy), watercourses (hydropower), the earth (geothermal energy), and generally from wet or dry biomass, on the scale of the lifespan of humanity. This is not the case for fossil and nuclear fuels.

They are mainly used for electricity generation and heating. These energies have very low pollution factors.

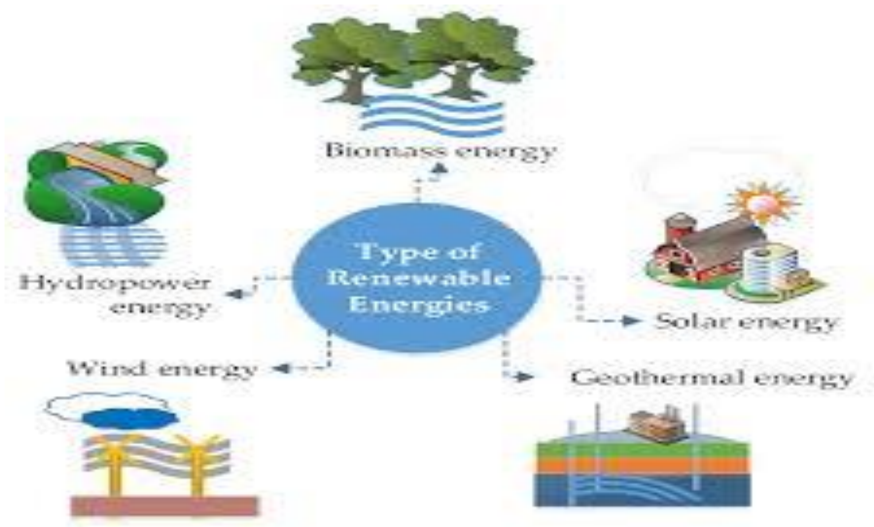

Figure 1.1: Energy types [2]

2.2.2.2. Non-renewable energies:

Energies are said to be non-renewable insofar as they are incapable of renewing themselves. The raw materials often used are hydrocarbons, uranium, etc. Non-renewable energies currently face major problems regarding reserves that are greatly decreasing, and nothing has yet been found to overcome these difficulties. Moreover, they present enormous dangers to the environment and to human health; this is the case, for example, with nuclear energy, which is very toxic. [2]

3 Essential principles in electrical energy:

Electrical energy is characterized by its enormous use in our current society due to its advantages and properties that make it more than necessary in our lives, and more efficient than others. We will attempt to present the most important elements that surround it.

3.1 General overview of electricity:

Electricity is one of the key drivers of progress. Its consumption is expected to increase by 85% by 2030. Today, electricity is used for lighting, heating, and air conditioning. It also powers electric motors that drive trains and operate household appliances.

It is a sector that has developed a position of global excellence in many fields, from production to all its applications. Throughout the entire value chain, the sector is a source of sustainable technological innovation, competitiveness, and employment. This is particularly true with new energy production sources such as wind and solar power, which use electricity as a means of delivering energy. [3]

3.1.1 Origin and history:

Electricity was discovered many centuries ago. Thales, a Greek scientist, is considered one of the first to observe electrical phenomena around the 6th century BC. He noticed that when a piece of amber was rubbed, it could attract other objects and sometimes produce sparks. He named this force “electricity.”

In 1799, the Italian researcher Alessandro Volta discovered a method to produce an electric current using his famous device, the Voltaic Pile. He invented the first electric battery, composed of alternating layers of silver and copper separated by paper.

Later, the French scientist André-Marie Ampère made important discoveries by distinguishing between voltage and electric current.

In 1826, Georg Ohm clarified the phenomenon of electrical conductivity in solid materials and established a definition of electrical tension (electromotive force) and its effect on conductors. In 1827, he formulated the fundamental relationship between current and voltage, known as Ohm’s Law: $U = R \times I$, where U is voltage, R is resistance, and I is current intensity.

In 1864, James Clerk Maxwell presented the theory of electromagnetism as a synthesis of all previous knowledge in the field.

The final major milestone was introduced by Albert Einstein through his theory of relativity, which helped explain electromagnetic phenomena in a broader physical context.

Electricity then developed progressively throughout the twentieth century, first in industry, public lighting, and railways, before becoming widely available in households. Different methods of electricity generation were developed, including hydroelectric, thermal, wind, and nuclear power plants. [4][5][6]

Figure 1.2:Dynamo Gramme (modèle de 1878) [6]

3.1.2. Definition of Electricity

The word “electricity” comes from the Greek word *electron*, meaning amber. The ancient Greeks discovered that when amber was rubbed, it could attract other objects and sometimes produce sparks. They therefore gave this force the name electricity.

Electricity is a physical phenomenon caused by the different electric charges present in matter, manifesting itself in the form of energy. The term electricity also refers to the branch of physics that studies the movement of electric charges, electrical phenomena, and their applications. Scientists consider electricity to be closely related to magnetism, which led to the creation of the field of electromagnetism, combining the study of electrical and magnetic phenomena.

It was during the 21st century that the properties of electricity began to be better understood. Mastering electricity contributed significantly to the emergence of the second industrial revolution.

Today, electrical energy is present everywhere. Produced from various energy sources such as hydroelectric, thermal, and nuclear energy, electricity is widely used in many domestic and industrial applications. [6]

3.2. Electrical Energy

3.2.1. Definition

Electrical energy is an essential factor in the development and evolution of human societies, whether in terms of improving living conditions or supporting industrial activities.

Electrical energy is a secondary form of energy obtained through the transformation of another type of energy known as primary energy. It is produced in the form of an electric current made up of moving electrons in order to generate light or heat. Electricity is considered an essential resource for economic agents because it is used for lighting, thermal comfort (heating and cooling), and as a factor of production. The official unit used to measure electricity is the kilowatt-hour (kWh).

The optimization and availability of electrical energy, together with electrical networks, make it possible to transport energy produced from decentralized sources to consumption points by transmitting large amounts of generated energy from a specific location. This is achieved through machines connected mainly to high-voltage levels, supplying consumers generally distributed across a given territory and connected to lower voltage levels.

This system also creates synergies between different production systems. Renewable sources such as hydroelectric, solar, and wind energy depend on the availability of the primary source, while thermal energy sources (conventional, nuclear, and geothermal) ensure base-load production and support for renewable systems. In the long term, it may also benefit from coordinated management across different time zones and energy networks.

3.3 Different Types of Electrical Energy Production

Power plants are responsible for producing electrical energy, or more precisely, for converting primary energy into electrical energy. Primary energy is the energy contained in a waterfall, a pile of coal, an oil reservoir, and similar natural resources.

There are different types of power plants:

- Fossil fuel power plants (coal, oil, and natural gas), also called conventional thermal steam power plants.
- Thermal combustion power plants (gas turbines).
- Nuclear power plants, which can also be considered thermal power plants.
- Hydroelectric power plants.
- Solar photovoltaic power plants.
- Wind power plants

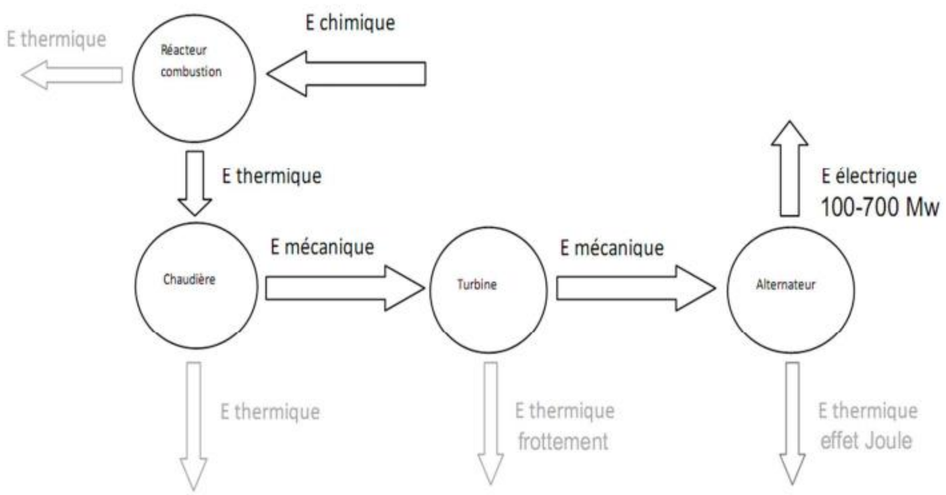

Figure 1.3: Electric Chaine [9]

3.3.1 Conventional Thermal Power Plants (Steam Power Plants):

A thermal power plant generates electricity by burning fuel (coal, gas, etc.) in a boiler that produces steam. This steam drives a turbine connected to an alternator.

The heat produced in the boiler by the combustion of coal, gas, or other fuels converts water into steam. This steam is then transported at high pressure and high temperature to a turbine. Under pressure, the turbine blades begin to rotate. Thermal energy is therefore converted into mechanical energy, which is then transformed into electrical energy through an alternator.

After leaving the turbine, the steam is converted back into water (condensation) by contact with cold surfaces, then returned to the boiler where the cycle starts again.

Thermal power plants convert the heat energy of fuel into mechanical energy and then into electrical energy.

Figure 1.4: Photograph of a thermal power plant [10]

The basic diagram of a steam thermal power plant includes the following components:

- A boiler, in which water is transformed into superheated steam.
- Connecting pipes used to transport steam from the boiler to the turbine.

- A multi-stage turbine that receives the superheated steam and rotates under its effect.
- A condenser that converts the steam leaving the turbine back into water by transferring part of its heat to circulating cooling water used for condensation (at atmospheric pressure).
- Connecting pipes used to transport the condensed liquid water from the condenser back to the boiler.

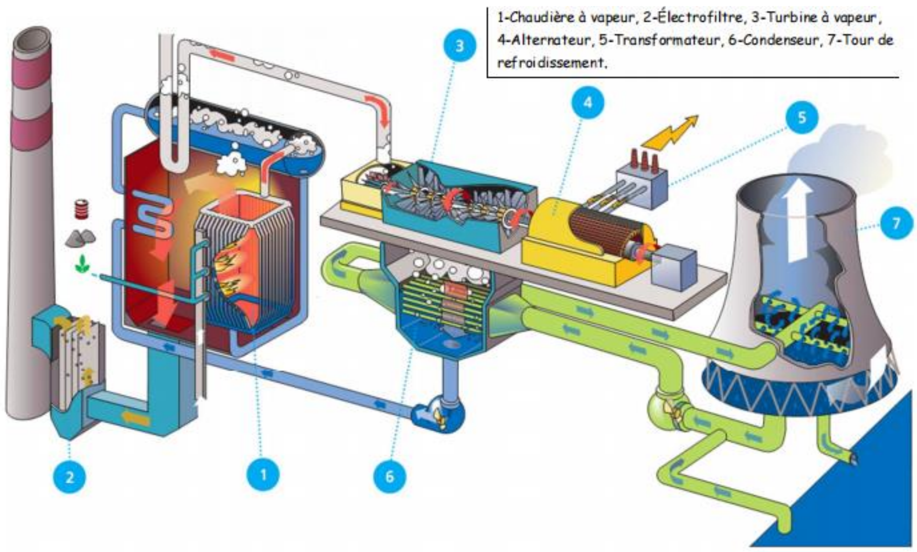

Figure 1.5: Schematic diagram of a conventional thermal power plant [9]

Thermal power plants convert the heat energy of a fuel into mechanical energy and then into electrical energy.

The basic structure of a steam thermal power plant includes the following components:

- A boiler, in which water is transformed into superheated steam.
- Connecting pipes used to transport steam from the boiler to the turbine.
- A multi-stage turbine that receives the superheated steam and rotates under its pressure.
- A condenser that converts the steam leaving the turbine back into water by transferring part of its heat to circulating cooling water used for condensation at atmospheric pressure.
- Connecting pipes used to transport the condensed liquid water from the condenser back to the boiler.

· The alternator, which is used to generate electrical energy. The turbine and alternator assembly is called a turbo-generator.

· A transformer substation, responsible for increasing the voltage produced by the alternator to match the transmission network voltage.**[9]**

a) Advantages:

- Well-mastered technology with low risk.

b) Disadvantages:

- Thermal power plants are highly polluting energy production systems.
    - They release large amounts of greenhouse gases into the atmosphere (mainly carbon dioxide, CO_2).
    - They are responsible for acid rain and air pollution.
- Depletion of natural resources (oil, gas).
- Low efficiency (35%).

3.2.2 Thermal power plants with combustion (gas turbines):

Gas turbines and turbojets can start up quickly, but their efficiency is limited. They are used as peak-load and backup units to cover unexpected demand peaks and to start in case of sudden failure of other generation units.

A gas turbine and a turbojet operate like a jet engine. They consist of a compressor, a combustion chamber, and a turbine. The compressor draws in air, compresses it, and injects it into the combustion chamber. Natural gas (in gas turbines) or kerosene (in turbojets) is injected there to be burned. The hot combustion gases drive the turbine, which in turn drives an alternator to produce electricity.**[9]**

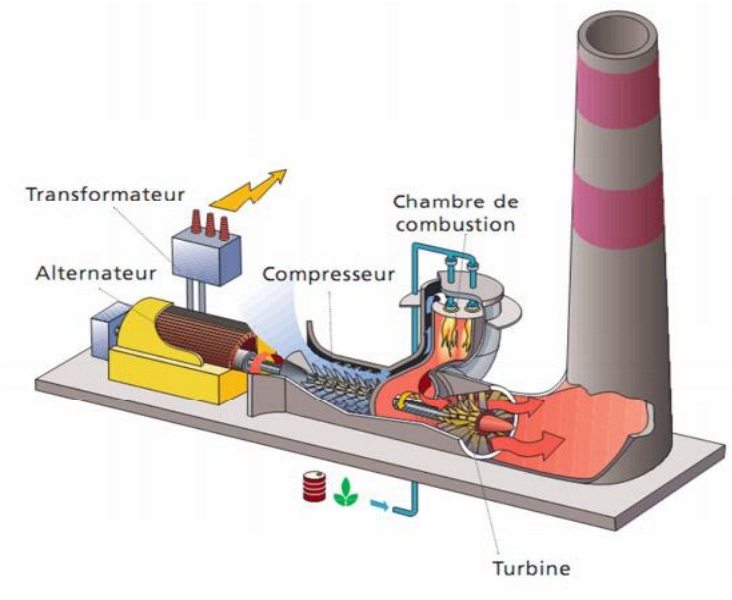

Figure 1.6: gaz turbin.[8]

a) Advantages :

- High specific power (kW/kg)
- Simple installation (the main requirement is the quality and volume of the intake air)
- High availability (>95%)
- Multi-fuel capability (gas, fuel oil, etc.)
- Requires little cooling fluid (water or air)
- Can operate in extreme climatic conditions (with adaptations to air intake and fuel and lubrication auxiliary systems)
- Fully automated operation and monitoring
- Fast start-up (a few tens of minutes)

b) Disadvantages :

- The compression ratio (and therefore efficiency) is limited by the number of compressor stages required.
- Significant drop in compressor efficiency at speeds lower than the nominal operating speed.
- Combustion temperature (and therefore efficiency) is limited by the mechanical strength of the turbine.

- Significant efficiency drop at partial load, especially for single-shaft machines.
- High machining cost of turbine blades.
- Unsuitable for frequent and gradual start-ups and shutdowns.
- Higher maintenance cost compared to diesel engines.
- Although under development, gas turbines cannot burn heavy fuel oil unlike diesel engines; they therefore use expensive fuels.

Its main drawback is its relatively low intrinsic thermal efficiency (≈30% to 35%), but this can often be offset by the possibility of using a low-cost fuel. However, recent technological advances have improved this efficiency (reaching 38% to 42%).

3.2.3 Nuclear power plants:

A nuclear power plant is an industrial facility that uses the fission of atomic nuclei to produce heat, part of which is converted into electricity (between 30% and 40%, depending on the temperature difference between the hot and cold sources). It is the main civil application of nuclear energy.

Figure 1.7: Photograph of a nuclear power plant in France.[10]

The first nuclear electricity production took place in 1951. Thus, in about twenty years, nuclear energy progressed from the understanding of its basic principles to practical demonstration. After this first application of nuclear energy for electricity production in the United States, the United Kingdom (1953), Russia (on June 27, 1954, the first civilian nuclear power plant was connected to the electrical grid in Obninsk in the Soviet Union), France (1956), and Germany (1961) followed suit. Thus, five countries exploited this energy source to generate electricity within the first decade following its practical demonstration.

Nuclear power plants can produce very large amounts of electricity from a very small quantity of fuel. A single nuclear fuel pellet of 2.5 cm produces as much energy as 807 kilograms of coal, 677 liters of fuel oil, or 476 cubic meters of natural gas.

Most reactors use a fuel containing uranium enriched to between 3% and 5% of uranium-235. Natural uranium (U-238) contains only about 0.7% uranium-235. Therefore, it is necessary to increase the concentration of uranium-235 to obtain a material suitable for use in nuclear reactors (this process is called enrichment).

Two industrial processes are currently used worldwide: gaseous diffusion and centrifugation.

An uranium-235 nucleus is bombarded by a neutron. This impact makes the U-235 nucleus unstable, causing it to split into two new nuclei: this is fission. This reaction releases a large amount of energy in the form of heat. New elements are produced… Fission products appear; these are called “fission products.” In addition to these elements, neutrons are also released.

The released neutrons mostly go on to strike other uranium nuclei, which in turn split and release additional neutrons: this is the chain reaction.**[9]**

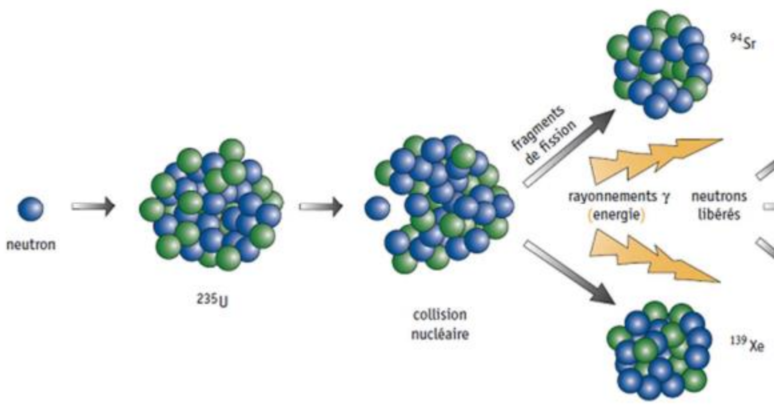

Figure 1.8: Principle of a chain reaction[9]

a)Advantages:

- Low-cost nuclear fuel.
- Independence from oil prices.
- Possibility of exporting electrical energy to neighboring countries.

b)Disadvantages:

- Risk associated with nuclear power plants (explosions, leaks, etc.).
- Storage of radioactive nuclear waste (the decay periods of radioactive elements vary greatly, up to several million years).
- Limited lifespan of nuclear power plants (20 to 30 years).

3.2.4 Hydroelectric power plants:

Water stored in dams or diverted through intake structures represents a form of potential energy (kinetic energy of water in motion) available to drive a hydraulic turbine in rotation.

Hydraulic energy is converted into mechanical energy by means of the turbine. The turbine is mechanically coupled to an alternator, which converts mechanical energy into electrical energy.

To best exploit the hydraulic potential of each country, each power plant must be adapted to its specific site (river characteristics, geographical, geological, and climatic conditions, etc.). Thus, each power plant has its own particular design.

Figure 1.9: Photograph of a hydroelectric power plant in Germany.[10]

owever, it is possible to classify hydroelectric power plants into three main categories according to the height of the water drop (and consequently the flow rate):

- High-head power plants
- Medium-head power plants
- Low-head power plants

A hydraulic turbine is a machine that converts into mechanical energy the energy provided by water as it flows from a higher altitude **ZA** to a lower altitude **ZB**. If **Q** is the water flow rate (in m^3/s), the theoretical power of a water drop is:

$$P = \rho Q g h$$

where:

ρ = the density of water (1,000 kg/m^3),
g = 10 m/s^2,
h = ZA – ZB (in meters).

This power, taking into account the efficiency of the turbine, is delivered to the alternator through its shaft.

The same power can be obtained:

- either with a high water head and a low flow rate (for example h = 1000 m and Q = 25 m³/s);
- or with a low water head but a high flow rate (for example h = 50 m and Q = 500 m³/s).

The generators (alternators) of this dam are connected to turbines driven by water falling from the reservoir.**[9]**

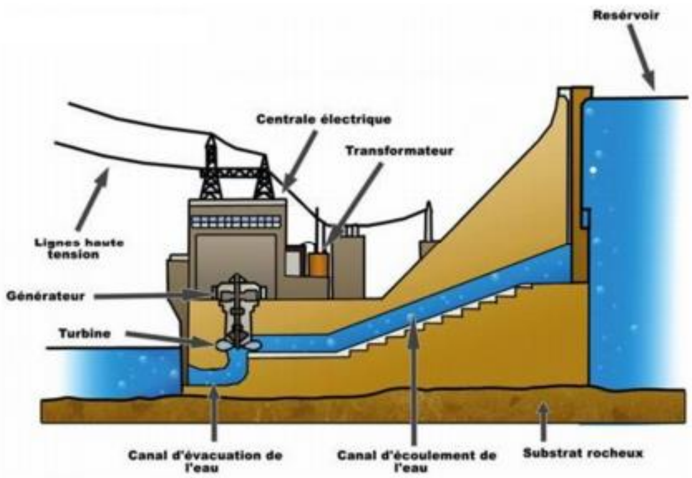

Figure 1.10: Cross-section of a hydroelectric dam [9]

a)Advantages:

- Renewable and clean energy source (no direct fuel combustion).
- Very low greenhouse gas emissions during operation.
- High efficiency compared to other power plants.
- Fast response to electricity demand (can quickly increase or decrease production).
- Helps regulate the electrical grid (especially high-head dams).
- Low operating costs once the plant is built.
- Long lifespan of installations (often several decades).
- Water reservoirs can also be used for irrigation, drinking water supply, and flood control.

b)Disadvantages:

- Electricity production depends strongly on rainfall and seasonal water availability.
- Water management must consider environmental impacts (wildlife, agriculture, ecosystems).
- Large dams can affect natural habitats and river ecosystems.
- High initial construction cost.

3.2.5 Solar or photovoltaic power plants

Conventional energy sources such as nuclear power or fossil fuels (coal, oil, and gas) come from limited stocks of materials extracted from the Earth's subsurface. Each of them, in their use, causes long-term environmental consequences of varying severity, which are increasingly being better controlled: air pollution, climate change, radioactive contamination, etc.

In contrast, renewable energy sources rely on natural flows that pass more or less continuously through the biosphere. If only a small fraction of these flows is used, then these energies remain harmless to the natural environment, both locally and globally. All renewable energy sources are directly or indirectly derived from the Sun.

Its direct radiation can be used in two ways:

- **Solar thermal panels:**
  These panels convert sunlight into heat. They are often used in domestic installations where they are connected to a water heater.
- **Photovoltaic solar panels:**
  More complex, they convert sunlight directly into electricity. Photovoltaic solar energy refers to electricity produced by converting part of solar radiation using a photovoltaic cell. Several cells are connected together to form a photovoltaic solar panel (or module). Several modules grouped together in a photovoltaic solar power plant form a photovoltaic field.

The term *photovoltaic* can refer either to the physical phenomenon—the photovoltaic effect—or to the associated technology.**[9]**

Figure 1.11: Photovoltaic cell – Photovoltaic panel [3]

a)Advantages:

- Solar energy is, on a human scale, inexhaustible and freely available in very large quantities. Moreover, during the operational phase, electricity production using photovoltaic panels is not polluting.
- Silicon, the material used in the most common solar panels, is very abundant and non-toxic.
- Solar panels have a lifespan of 25 to more than 30 years and are almost fully recyclable.
- The modularity of panels is very high, meaning it is possible to design systems of various sizes in many different environments. They are therefore well suited for decentralized electricity production in isolated areas.
- Photovoltaic panels can be used on a small domestic scale (e.g., rooftop solar systems) or for large-scale industrial energy production (e.g., solar farms).

b)Disadvantages:

- Photovoltaic technology is still too expensive to be competitive with fossil fuels; its cost per kilowatt-hour is about four times higher.
- The most widely used photovoltaic panels, made of crystalline silicon, are heavy, fragile, and difficult to install.
- A power plant requires large areas of land. For example, a 550 MW project covers an area of about 25 km².

- The environmental and energy impact of manufacturing silicon panels is significant. A photovoltaic cell must operate for at least five years to compensate for the energy used in its production.
- Electrical energy cannot be stored “directly” in its primary form. It can only be stored “indirectly” in batteries (chemical form) or in kinetic accumulators (mechanical form). Existing storage technologies are still very expensive.

3.2.6 Wind power plants:

A wind turbine uses the energy of the wind. The mechanical energy of the wind turns the blades, which act as the turbine of the wind turbine and drive an alternator as well.

A portion of the rotational mechanical energy of the blades is thus converted by the alternator into electrical energy.

Figure 1.12: Photograph of a wind power plant in England.[10]

a)Advantages:

- Wind energy is clean and can be combined with photovoltaic panels and storage batteries to optimize electricity supply.

b)Disadvantages:

- Wind energy exploitation itself is non-polluting, but wind turbines generate noise pollution due to blade rotation and also contribute to landscape degradation.

  .
- Low availability (20–30%) and difficulties in connecting to the electrical grid.
- Large land use requirement.
- Public acceptance issues.

4 energy consumption in Algeria :

Electricity can be generated in two main ways: by harnessing the heat from burning fuels or nuclear reactions in the form of steam (thermal power) or by capturing the energy of natural forces such as the sun, wind or moving water.

4.1 General Overview of Energy Consumption in Algeria:

Electricity production in Alggeria tends to closely match the country demand, which in turn is driven by economic and population growth, upgrades and changes to the structure of the economy following the centry development and needs of total of : 95627 GWh

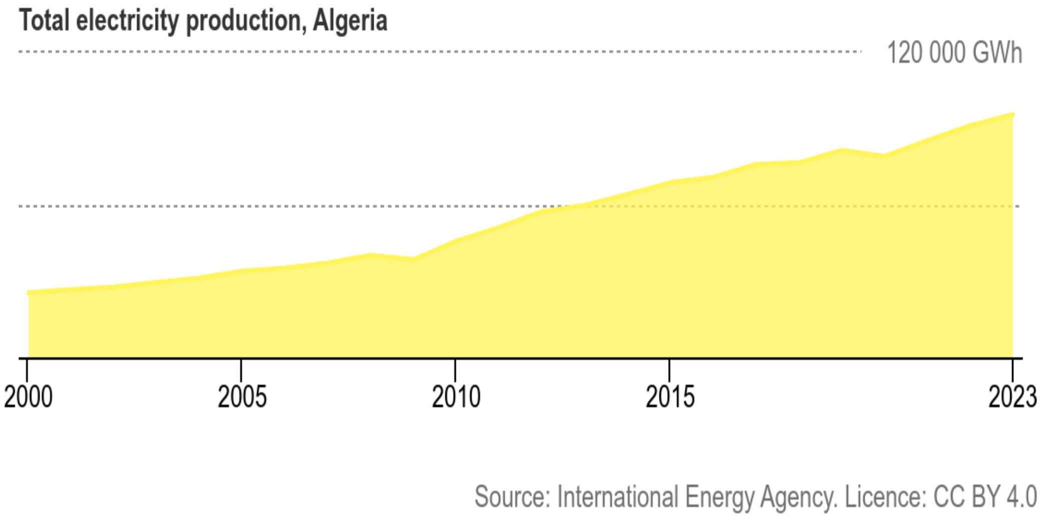

Figure 1.13 : total electricity production in algeria 2000-2023. [4]

4.2 Main Sources of Electrical Energy Production in Algeria:

Largest source of electricity generation in Algeria is Natural gas of **99%** of total generation

In Algeria, natural gas represents the principal source of electricity generation. The national power sector relies heavily on gas-fired power plants due to the country's significant natural gas reserves and its well-developed gas infrastructure.

The extensive use of natural gas in electricity production provides advantages such as stable energy supply, relatively efficient generation processes, and the availability of domestic resources. However, this strong dependence also creates challenges related to energy diversification and environmental sustainability.

To address these challenges, Algeria has shown increasing interest in the development of renewable energy sources, particularly solar energy, in order to diversify its electricity mix and reduce long-term reliance on fossil fuels.[4]

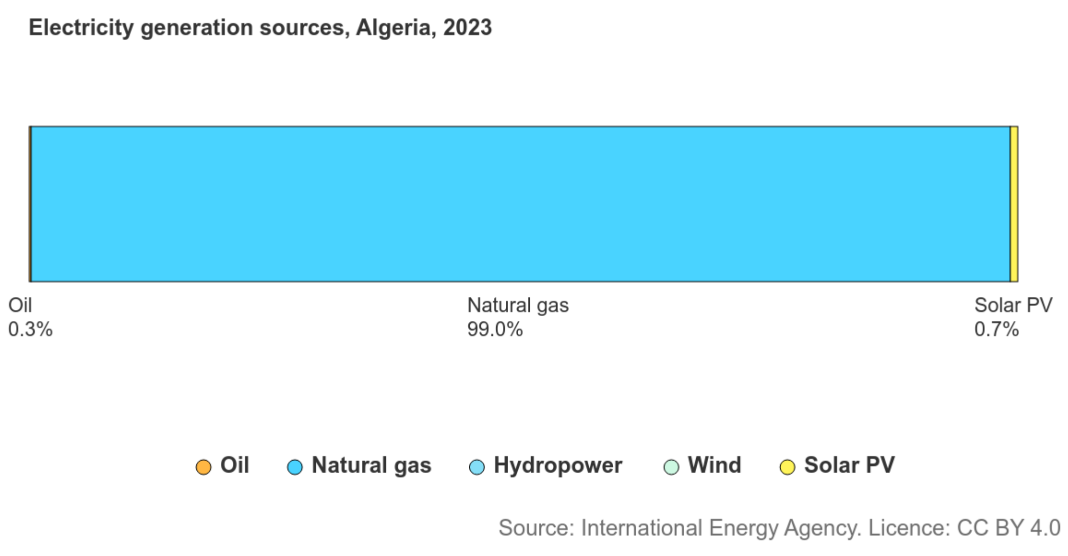

Figure 1.14: electricity source in Algeria. [4]

4.3 Impact of Population Growth and Urbanization :

Algeria's energy system is increasingly exposed to the impacts of climate change and extreme weather conditions. In recent years, critical energy infrastructure has suffered disruptions caused by heatwaves, flash floods, droughts, and wildfires. Since climate projections indicate that Algeria will warm faster than the global average, these environmental risks are expected to intensify in the coming decades. Consequently, improving the resilience of the national energy system has become a strategic priority for the country.

4.3.1 temperature :

Between 2000 and 2023, Algeria experienced a significant rise in average surface temperatures, with an increase of approximately 0.49 °C per decade. This rate of warming is considerably higher than the global average, estimated at 0.37 °C per decade during the same period. The continuous increase in temperature has strongly influenced both climate conditions and national energy consumption patterns.

One of the most visible impacts of this warming trend is the growing demand for cooling systems. Cooling degree days (CDDs), which are used to measure the need for air conditioning, increased by nearly 35% in Algeria between 2000 and 2023, representing more than 100 additional CDDs per decade. This increase exceeds the global average growth rate of approximately 25%, demonstrating the strong effect of rising temperatures on electricity demand in the country.

In contrast, heating degree days (HDDs), which indicate the demand for heating energy, declined steadily during the same period at a rate of nearly 70 HDDs per decade. This reduction reflects the gradual decrease in heating requirements due to warmer climatic conditions. Consequently, Algeria's energy consumption profile is progressively shifting toward higher electricity usage for cooling, especially during prolonged summer heatwaves. **[5]**

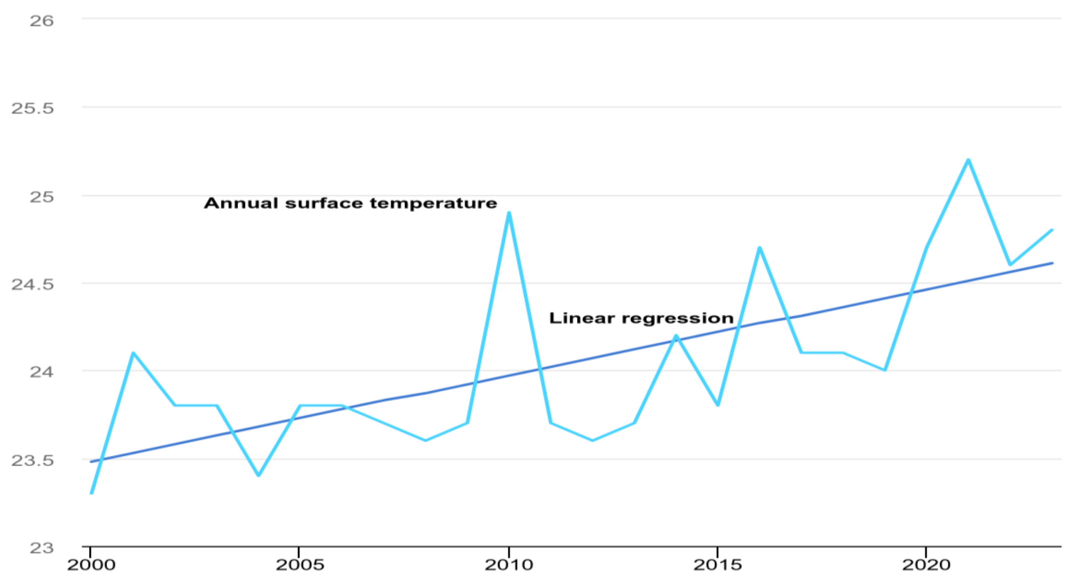

Figure 1.15: temperature changes in Algeria 2000-2020.[5]

4.4Challenges of Energy Management in Algeria :

Energy management in Algeria faces several important challenges due to the rapid growth of electricity demand, population increase, urbanization, and climate change effects. The country depends heavily on natural gas for electricity production, which limits energy diversification and increases environmental concerns. In addition, rising temperatures and the widespread use of air conditioning place significant pressure on the national electrical grid, especially during peak periods. Algeria also faces challenges related to infrastructure modernization, renewable energy integration, and improving energy efficiency. Therefore, developing intelligent energy management and forecasting systems has become essential to ensure energy security and sustainable development [5].

5. Overview of Electricity Consumption Forecasting:

5.1 Types of Electricity Forecasting :

Usually electricity forecasting can be classified into three main fields depending on the prediction horizon of each one :

5.1.1 Short-Term Forecasting (STLF):

Predicts electricity demand from a few minutes up to several days ahead. It is mainly used for real-time grid management, load balancing, and operational control.

·5.1.2 Medium-Term Forecasting (MTLF):

Predicts electricity consumption from weeks to months ahead. It is useful for maintenance scheduling, fuel purchasing, and energy trading.

·5.1.3 Long-Term Forecasting (LTLF):

Predicts electricity demand over several years. It supports strategic planning, infrastructure development, and policy decision-making in power systems. [10]

5.2 Challenges in Electricity Consumption Prediction:

Electricity consumption prediction faces several challenges due to the complex and dynamic nature of energy demand. Consumption patterns are influenced by multiple factors such as weather conditions, human activities, economic changes, seasonal variations, and special events. Data quality issues including missing values, noisy measurements, and inconsistent sensor readings can also reduce prediction accuracy. In addition, large-scale datasets require high computational resources and efficient learning models. Another major challenge is capturing long-term temporal dependencies and sudden fluctuations in electricity usage. [11]

6. Deep Learning Models for Electricity Forecasting:

Over the recent years, researchers have focused on developing cutting-edge technologies and algorithms for electricity consumption . These studies are constantly contributing to the improvement of this field. Furthermore, with the advent of machine learning techniques, there has been a growing interest in using diverse strategies for appropriate counter-measures, after a review of various studies concerning the issue.

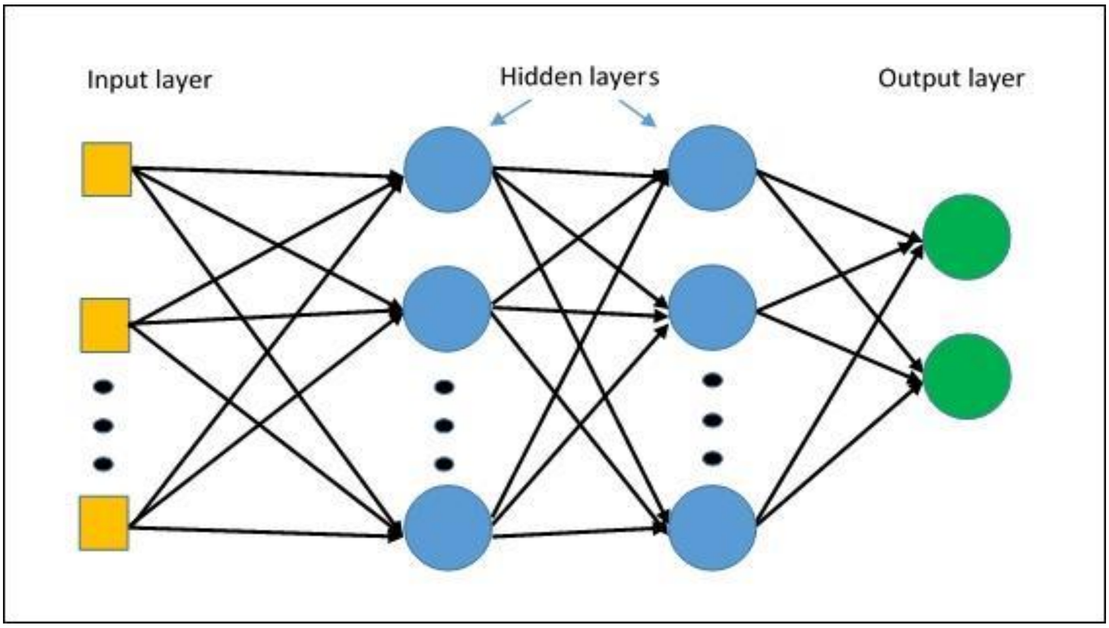

Figure 1.16: The Structure of Multi-layer Perceptron.[12]

The fundamental component of a feedforward neural network is the neuron. A neuron receives input signals either from external data sources or from other neurons within the network. It processes these inputs through mathematical computations and generates an output value. This output is then transmitted to neurons in the subsequent layer, allowing information to flow forward through the network until the final prediction or result is produced at the output layer.

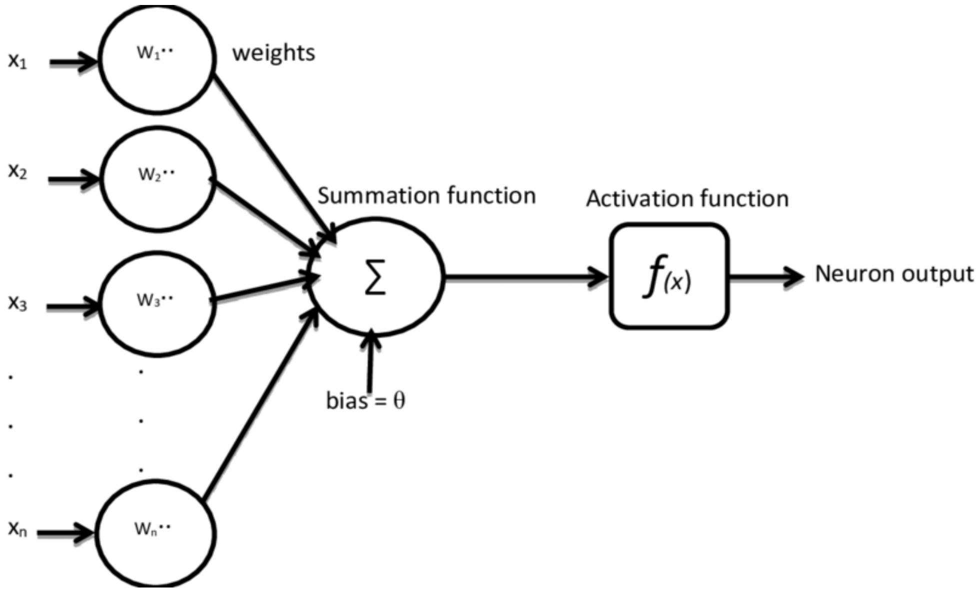

Figure 1.17: The structure of the artificial neuron. [12]

6.1 Long Short-Term Memory (LSTM) Networks:

A Long Short-Term Memory (LSTM) network is a type of recurrent neural network (RNN) specifically developed to overcome the long-term dependency problem encountered in traditional RNNs. In an LSTM architecture, the hidden neurons of a conventional RNN are replaced by memory cells. These memory cells include three main components: the input gate, the forget gate, and the output gate. This structure enables the network to selectively retain important information while discarding irrelevant or erroneous data at each time step.

Due to its strong ability to capture temporal dependencies, the LSTM network has become one of the most effective deep learning models in several fields, including speech recognition and language translation. Temporal relationships are also highly present in electrical power consumption data, as electricity usage patterns are influenced by human behavior, making them complex and difficult to predict accurately. In electrical load forecasting applications, the LSTM model is designed to learn consumption patterns from historical load profiles, preserve relevant information in its memory cells, and generate future load predictions based on the acquired knowledge [9].

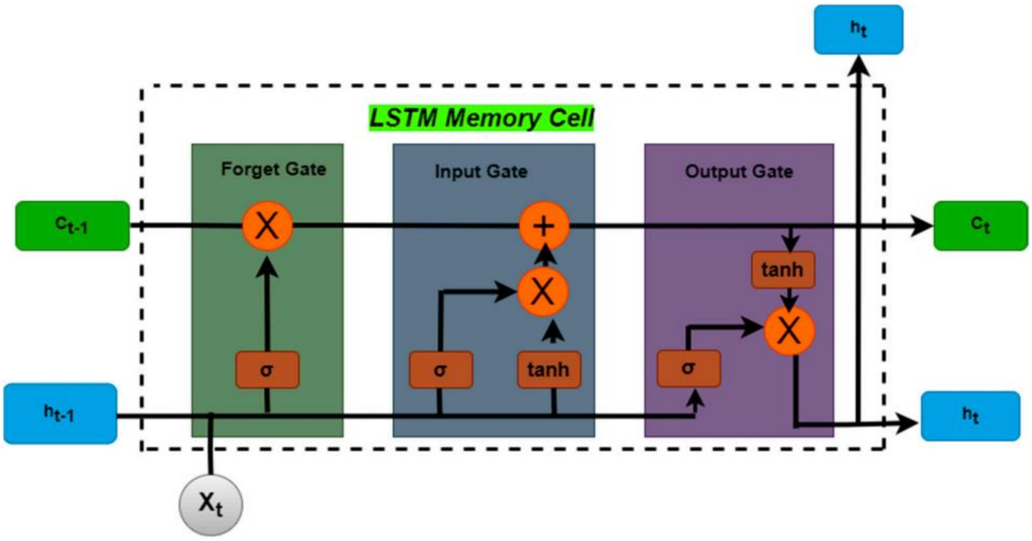

Figure 1.18: LSTM Memory Cell.[9]

6.2 Recurrent Neural Network (RNN) Model

Recurrent Neural Networks (RNNs) are deep learning models specifically developed for processing sequential and time-series data. They have been widely applied in several domains such as speech recognition, machine translation, and image caption generation. Unlike traditional neural networks, RNNs possess a memory mechanism that allows information from previous time steps to influence the processing of current inputs.

In an RNN architecture, data are processed sequentially, where each input vector is analyzed step by step while preserving information from earlier states through hidden layers. This recurrent structure enables the network to capture temporal dependencies and patterns within sequential data.

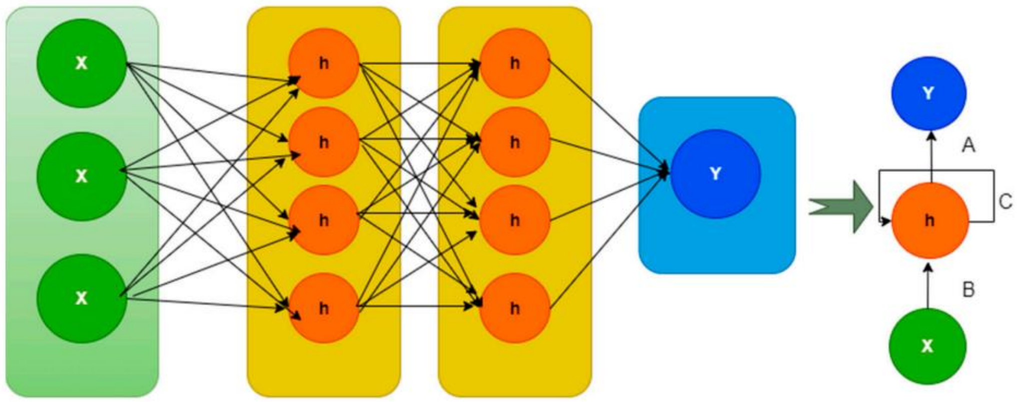

Figure 1.19: RNN Architecture.[9]

Figure 17 illustrates the structure of an RNN model, where “x” denotes the input layer, “h” represents the hidden layer, and “y” corresponds to the output layer. The network parameters A, B, and C are used to optimize the learning process and improve prediction performance. At each time step ttt, the hidden state is determined using both the current input x(t)x(t)x(t) and information obtained from the previous time step x(t−1)x(t-1)x(t−1). The generated output is then fed back into the network, allowing the model to continuously update its internal state and enhance future predictions.

6.3 Gated Recurrent Unit (GRU) Model

The Gated Recurrent Unit (GRU) is a gating mechanism used in recurrent neural networks, introduced in 2014 to improve the performance of traditional RNN architectures . The GRU shares similarities with the Long Short-Term Memory (LSTM) network but has a simpler structure and fewer parameters because it does not include a separate output gate. This reduced complexity allows GRU models to train faster while maintaining strong prediction capabilities.

Several studies have shown that GRU networks can outperform LSTM models in specific applications such as speech signal processing, polyphonic music generation, and natural language processing tasks . In addition, GRUs have demonstrated superior performance when working with smaller or less frequent datasets .

As an enhanced version of the classical RNN hidden layer, the GRU architecture is illustrated schematically in Figure . A GRU cell mainly consists of three components: the update gate, the reset gate, and the candidate hidden state. These mechanisms enable the network to efficiently preserve useful information and discard irrelevant data during the learning process.

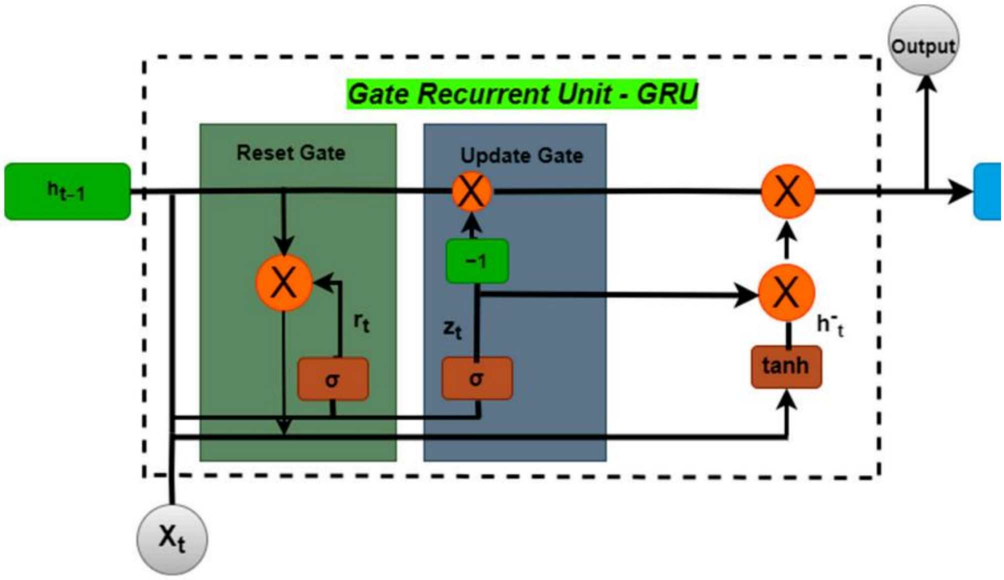

Figure 1.20: GRU Archetecture. [9]

7. Synthesis:

In the preceding section on related works, we discussed several studies and investigations focused on electricity consumption forecasting, abnormal energy demand detection, and smart grid management. These works used different artificial intelligence techniques, including machine learning and deep learning models, to improve prediction accuracy and support energy management decisions.

Based on our findings, deep learning methods are among the most effective approaches for time-series forecasting, especially when dealing with complex and changing electricity consumption patterns. In particular, recurrent neural network models such as GRU and LSTM have shown strong performance because they can learn from historical data and understand temporal dependencies.

Therefore, our proposed method focuses on using a GRU-based deep learning model to predict electricity consumption for multiple buildings over the next six hours. The system uses historical electricity readings, time features, weather data, and building information to forecast future demand. In addition, the project includes an abnormal increase detection mechanism to identify unusual consumption behavior.

The main objective of this work is not only to predict electricity usage, but also to support decision-making during possible city-wide power shortages. By classifying buildings according to their importance, such as healthcare, education, emergency services, and other public facilities, the system can help prioritize critical buildings and recommend load reduction for less critical ones. This can contribute to a smarter load-shedding strategy that protects essential services during electricity shortages.

Possible research areas for developing this AI-based system include:

Critical infrastructure protection: Hospitals, emergency centers, schools, and public service buildings require continuous electricity. AI can help ensure that these buildings are prioritized during power shortages.

Smart load-shedding management: During a city-wide electricity shortage, the system can help decide which buildings should reduce consumption first while keeping important buildings powered.

Abnormal consumption detection: Sudden increases in electricity usage can create pressure on the grid. Detecting these abnormal increases early can help prevent overloads and improve energy stability.

Urban energy forecasting: In large cities, electricity demand changes depending on time, weather, and building type. Deep learning forecasting models can help predict these changes and support better energy planning.

8. Conclusion:

In conclusion, our project proposes an AI-based electricity forecasting and priority load-shedding system using deep learning. The system aims to predict future electricity consumption, detect abnormal increases, and support the protection of critical buildings during power shortage situations.

Chapter 2: Conceptual Study

Chapter 2: Conceptual Study

1.Introduction :

As demonstrated in the preceding chapters, numerous techniques have been proposed for electricity consumption forecasting in order to improve energy management and optimize power usage in modern buildings. With the increasing availability of smart-meter data and artificial intelligence technologies, automatic forecasting systems have become an efficient solution for predicting short-term energy demand in a timely and cost-effective manner.

However, due to the complexity and variability of building energy consumption patterns, the performance of forecasting models may vary depending on several factors such as weather conditions, occupancy behavior, seasonal variations, and data quality. In addition, the large-scale and dynamic nature of energy datasets presents significant challenges for achieving highly accurate predictions in real-time applications.

Therefore, in this work, we proposed a GRU-based deep learning approach aimed at addressing these challenges and improving the accuracy and reliability of short-term electricity consumption forecasting. The proposed model integrates historical electricity usage, temporal information, weather variables, and building identity embeddings to better capture consumption behavior patterns and enhance prediction performance. Furthermore, an abnormal electricity consumption detection system was implemented to identify unusual increases in energy usage and support intelligent energy monitoring.

2.Comparative Analysis of Models :

Model	Dataset	Features	Metric	Accuracy	Advantages
LSTM	UCI Dataset:The UCI Household Electric Power Consumption dataset is a famous public dataset containing: household electricity usage, voltage, current, timestamps	Previous electricity consumption + Temperature.	RMSE	High	Long-term memory
GRU	Smart Meter: Smart meter datasets contain real-time electricity readings collected from smart electricity meters	Consumption only: uses only historical electricity usage.	MAE	Medium-High	Faster training
RNN	UCI Dataset: The UCI Household Electric Power Consumption dataset contains household electricity usage, voltage, current, and timestamps.	Previous electricity consumption data.	RMSE	Medium	Simple sequential learning

Table 2.1:Comparative Analysis of Models.

3.Comparative Analysis of Existing Works :

Authors / Year	Model Used	Dataset	Features Used	Evaluation Metrics	Main Results / Findings
Daniel L. Marino et al. (2016)[13]	LSTM, Seq2Seq LSTM	Residential building energy dataset	Historical electricity load	RMSE	LSTM performed well for hourly forecasting, while Seq2Seq improved minute-level prediction.
Anupiya Nugaliyadde et al. (2019)[14]	RNN, LSTM	London Smart Meter Dataset	Previous electricity consumption	RMSE	Both RNN and LSTM achieved strong forecasting performance with RMSE around 0.1.
Sameh Mahjoub et al. (2022) [15]	LSTM, GRU, Drop-GRU	Smart grid energy data	Historical power load	MAE, RMSE	Drop-GRU and multi-layer GRU improved short-term forecasting accuracy compared to traditional LSTM.
Saad Emshagin et al. (2022) [16]	Customized LSTM, GRU	Household smart meter dataset	Electricity consumption data	MAE, RMSE	LSTM produced better household forecasting accuracy than GRU and ARIMA models.
Nuno Oliveira et al. (2022) [17]	CNN, LSTM, CNN-LSTM, TCN	Manufacturing energy dataset	Instant energy consumption	RMSE	TCN achieved the most reliable short-term forecasting results.
Jerry I. Teleron et	CNN-LSTM-	Hourly energy	Univariate	Forec	Transformer-enhanced

al. (2025)[18]	Transformer	demand dataset	load series	asting accuracy	CNN-LSTM significantly improved prediction performance.
Vasileios Pentsos et al. (2025)[19]	Hybrid LSTM-Transformer	Power load forecasting dataset	Historical load sequences	MAE, RMSE	Hybrid Transformer-LSTM architecture outperformed standalone models.
Shwetha B N et al. (2025)[20]	CNN-BiLSTM, CNN-TFT	Residential electricity dataset	Multivariate temporal features	RMSE	Hybrid CNN-BiLSTM and Temporal Fusion Transformer improved residential forecasting accuracy.

Table 2.2:Comparative Analysis of Existing Works.

4.System Design :

In this study, we propose a deep learning-based electricity forecasting and critical building protection system using a GRU neural network. The system predicts electricity consumption for the next six hours using historical electricity data, weather information, time features, and building metadata.

After training and testing the model, its performance is evaluated using MAE, RMSE, MAPE, and R^2 score. Once reliable results are achieved, the model can be integrated into a smart energy management platform.

During a city-wide power shortage, the system compares predicted demand with available supply. If a shortage risk is detected, buildings are classified by priority. Critical buildings such as hospitals, healthcare centers, schools, and emergency facilities remain powered, while less critical buildings are selected for load reduction.

The system also detects abnormal electricity increases and sends alerts to the control center, helping prevent full power cuts and protect essential services.

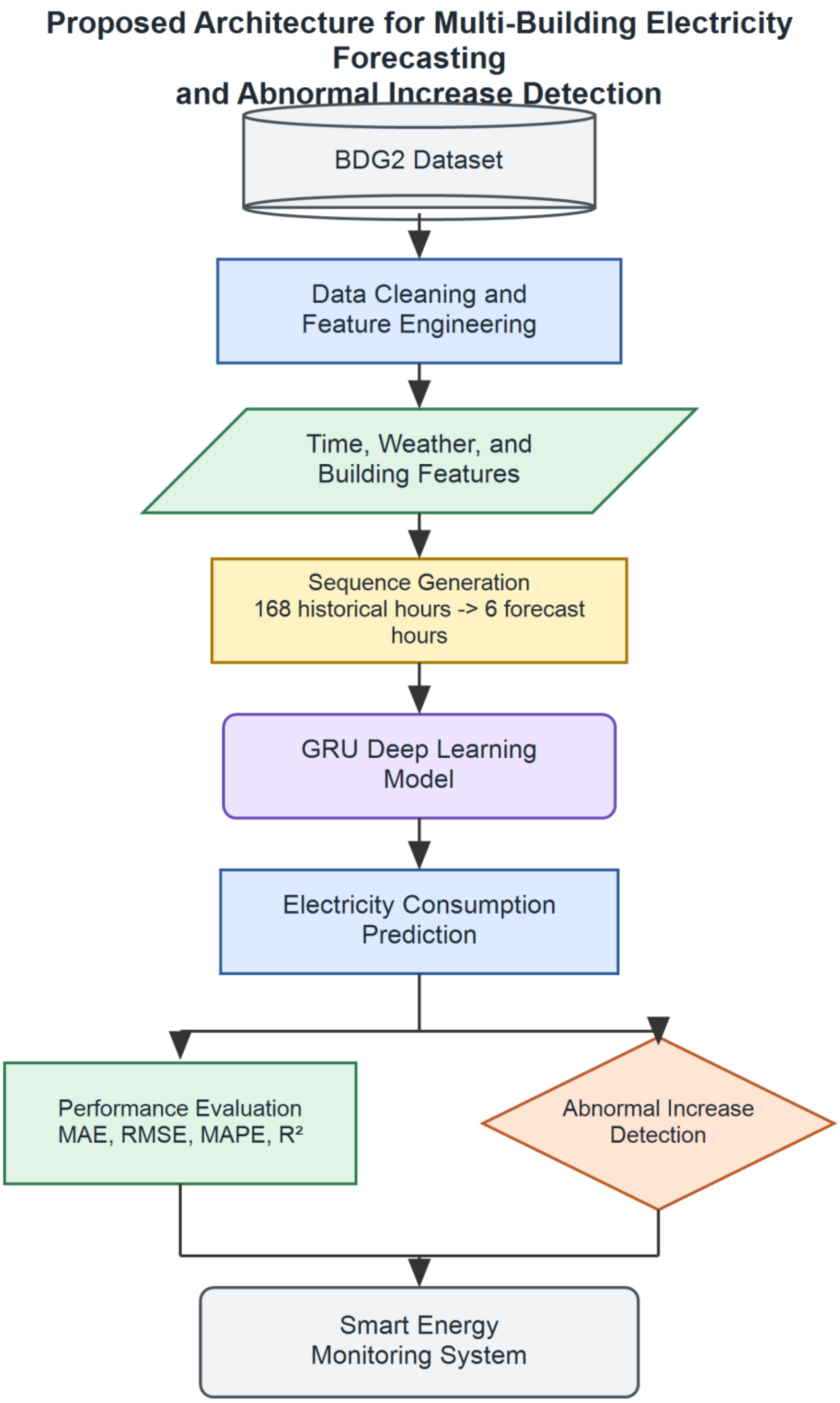

Figure 2.1: system archetecture.

5. Presenting Dataset

In this section, we're presenting the dataset used to train the model of the proposed system.

The proposed intelligent electricity consumption forecasting system is developed using the Building Data Genome Project 2 (BDG2) Dataset, an open-access large-scale dataset designed for building energy analysis and machine learning research.

The Building Data Genome Project 2 (BDG2) is a comprehensive real-world dataset containing hourly energy consumption measurements collected from non-residential buildings distributed across multiple regions in North America and Europe. The dataset was introduced as part of the ASHRAE Great Energy Predictor III competition and has become a benchmark dataset for energy forecasting, anomaly detection, and smart building analytics research.

The dataset includes energy meter readings, weather information, and detailed building metadata, making it highly suitable for deep learning applications such as Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU) architectures.[24]

5.1Dataset Characteristics

The BDG2 dataset contains:

- 1,636 non-residential buildings
- 3,053 energy meters
- Approximately 53.6 million hourly measurements
- Data collected over two full years (2016–2017)
- Hourly temporal resolution
- Multiple energy meter categories including:
    - Electricity
    - Chilled water
    - Hot water
    - Steam
    - Irrigation water

- Solar energy

Each meter provides continuous hourly energy consumption values, enabling the study of both short-term and long-term energy usage behavior.

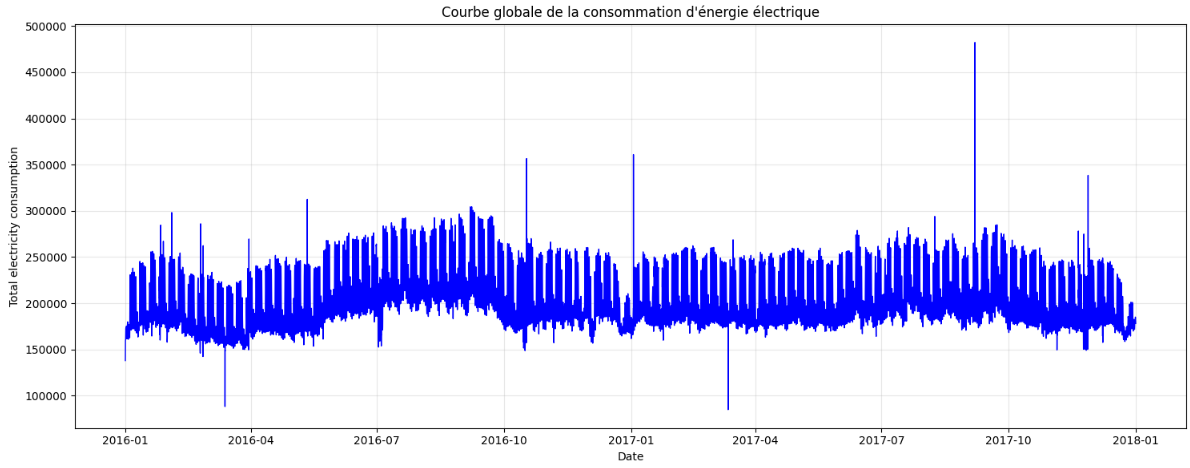

Figure 2.2: The electricity consumption database curve

5.2 Data Structure:

The dataset used in this study is the Building Data Genome Project 2 (BDG2), which contains historical electricity consumption records collected from multiple buildings. For this work, 50 buildings were selected from the dataset for analysis and model development. The data is organized as hourly time-series measurements, where each entry represents the electricity consumption of a specific building at a particular time.

The dataset includes electricity meter readings, building metadata, and weather-related information. Electricity consumption values are considered the primary target variable, while temporal features, weather conditions, and building characteristics are utilized as input features for the forecasting process. The dataset is chronologically divided into training, validation, and testing subsets. Approximately 50% of the data is allocated for training, 25% for validation, and the remaining 25% for testing.

The proposed forecasting model uses the previous 168 hours of historical data, corresponding to one week, to predict electricity consumption .

6 .Model Architecture:

6.1 Electricity Prediction Model (EPM):

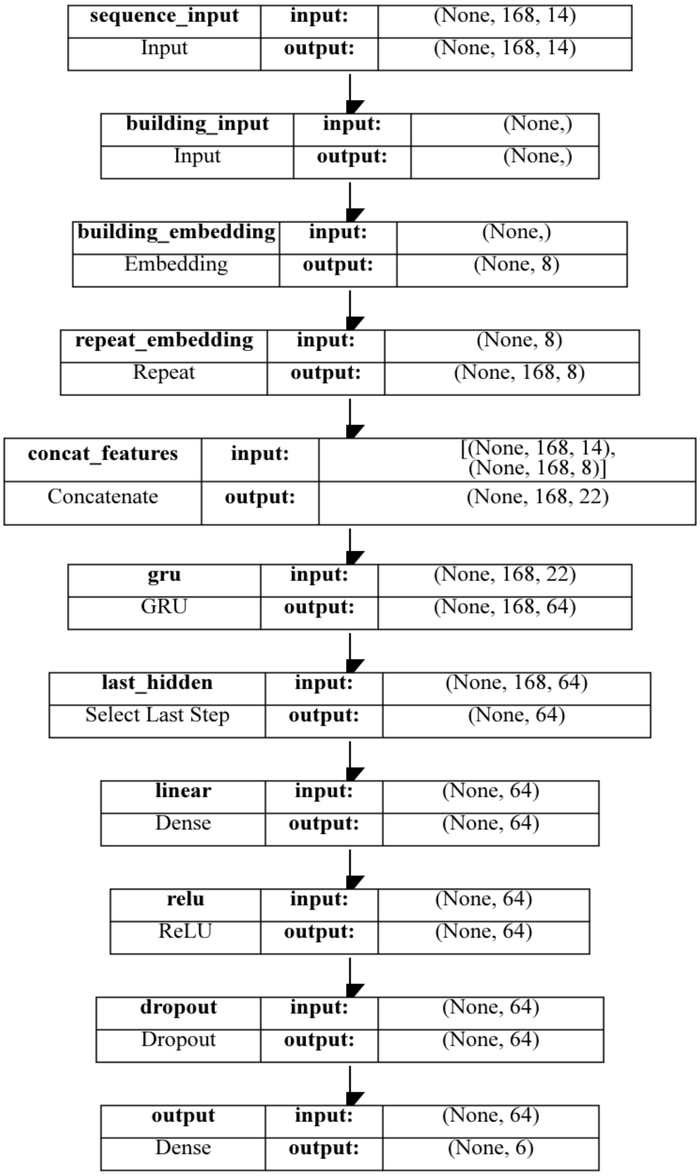

Figure 2.3: Electricty Prediction Model.

In this subsection, we will explain the function of each layer type employed in the architecture of our GRU model, as illustrated in the figure.

Model architecture

- **model** = FinalGRUForecaster()
- **sequence_input** = Input(shape=(168, 14))
- **building_input** = Input(shape=(1,))
- **building_embedding** = Embedding(num_buildings, 8)(building_input)
- **repeat_embedding** = RepeatVector(168)(building_embedding)
- **concat_features** = Concatenate()([sequence_input, repeat_embedding])
- **gru** = GRU(64, return_sequences=True)(concat_features)
- **last_hidden** = Lambda(lambda x: x[:, -1, :])(gru)
- **linear** = Dense(64)(last_hidden)
- **relu** = ReLU()(linear)
- **dropout** = Dropout(0.10)(relu)
- **output** = Dense(6)(dropout)

Figure 2.4: Model Creation.

● **'sequence_input':** This input layer receives sequential electricity consumption data with a shape of (168, 14), where 168 represents the previous 168 hours (one week) of historical observations and 14 corresponds to the number of input features used by the model. These features include electricity consumption values, temporal features such as hour, day, and month encodings, as well as weather-related information. This layer serves as the primary source of sequential information for the forecasting process.

● **'building_input':** This input layer receives the building identifier associated with each electricity consumption sequence. Since the proposed framework is designed to learn from multiple buildings simultaneously, the building identifier helps the model distinguish between different building consumption behaviors and operational characteristics.

● **'building_embedding':** The embedding layer transforms each building identifier into a dense vector representation of size 8. Instead of using raw categorical building IDs, the embedding layer learns hidden numerical representations that capture similarities and unique patterns between buildings. This enables the model to better generalize across multiple building types and improve forecasting accuracy.

● **‘repeat_embedding’:** This layer repeats the learned building embedding vector across all 168 timesteps of the input sequence. As a result, the building-specific information becomes available at every timestep of the sequential input, allowing the temporal forecasting model to jointly learn time-series patterns and building characteristics.

● **‘concat_features’:** The concatenation layer combines the sequential input features with the repeated building embeddings. The original input sequence shape of (168, 14) is merged with the repeated embedding shape of (168, 8), producing a combined feature representation of shape (168, 22). This enriched representation contains electricity consumption data, temporal information, weather features, and building identity information simultaneously.

● **‘gru’:** The GRU layer is the core component of the forecasting architecture. It contains 64 hidden units and is responsible for learning temporal dependencies and sequential patterns from the historical electricity consumption data. The GRU processes the combined feature representation over 168 timesteps and generates hidden state representations that capture both short-term and long-term consumption behaviors. The parameter ‘return_sequences=True’ allows the GRU layer to output hidden representations for all timesteps in the sequence.

● **‘last_hidden’:** This operation selects the hidden representation corresponding to the final timestep of the GRU output. The extracted vector has a size of 64 and acts as a compact summary of the previous week of electricity consumption patterns, temporal trends, weather effects, and building characteristics. This summarized representation is then used for forecasting future electricity demand.

● **‘linear’:** This fully connected dense layer contains 64 neurons and transforms the GRU output into a higher-level feature representation suitable for forecasting. The layer helps the model learn more complex nonlinear relationships between the learned temporal features and the target electricity demand.

● **'relu':** The Rectified Linear Unit (ReLU) activation function is applied after the dense layer to introduce nonlinearity into the model. The ReLU activation improves the network's ability to learn complex and nonlinear electricity consumption patterns while also helping reduce the vanishing gradient problem during training.

● **'dropout':** The dropout layer uses a dropout rate of 0.10, meaning that 10% of the neurons are randomly deactivated during training. This regularization technique helps prevent overfitting and improves the generalization capability of the model when applied to unseen electricity consumption data.

● **'output':** The final dense output layer contains 6 neurons corresponding to the forecasting horizon of the model. This layer generates predictions for the next 6 hours of electricity consumption simultaneously. Each neuron represents the predicted electricity demand for one future timestep.

The proposed GRU-based architecture combines sequential electricity consumption data, weather information, temporal encodings, and building embeddings to accurately model complex energy consumption behaviors across multiple buildings. The GRU layer enables the framework to capture temporal dependencies efficiently, while the embedding mechanism allows the model to learn building-specific characteristics. Furthermore, the use of dense layers, ReLU activation, and dropout regularization improves the forecasting capability and robustness of the proposed system for short-term electricity consumption prediction and intelligent energy management applications.

6.2 EP Model Configuration and parameterization:

6.2.1 Loss Function :

We implemented the Smooth L1 loss function, also known as the Huber loss, which is commonly used in regression-based deep learning models. This loss function is particularly effective for time-series forecasting tasks where the data may contain noise and outliers, such as electricity consumption measurements in multi-building environments.

The Smooth L1 loss function is defined as:

$$\mathcal{L}_{\text{smooth L1}} = \frac{1}{N} \sum_{\iota=1}^{N} \begin{cases} \frac{1}{2}(\text{yi} - \widehat{y_\iota})^2 & \text{IF } |\text{yi} - \text{yi}| < 1 \\ |\text{yi} - \widehat{y_\iota}| - \frac{1}{2} & \text{otherwise} \end{cases} \quad \text{....1}$$

where yi represents the actual value of the i^{th} sample, $\widehat{y_\iota}$ is the predicted value, and *N* is the total number of samples.

The first part of the function, $\frac{1}{2}(\text{yi} - \widehat{y_\iota})^2$, behaves like the Mean Squared Error (MSE) and penalizes small prediction errors more strongly, encouraging precise learning in normal operating conditions. The second part, $|\text{yi} - \widehat{y_\iota}| - \frac{1}{2}$, behaves like the Mean Absolute Error (MAE) and reduces the influence of large errors, making the model more robust to abnormal spikes and sudden changes in electricity consumption.

In other words, the Smooth $L1$ loss function provides a balance between sensitivity to small errors and robustness to outliers. This makes it highly suitable for electricity forecasting problems where consumption patterns may include irregular peaks caused by unusual or abnormal building usage.

The objective of the training process is to minimize this loss function so that the model can accurately learn temporal dependencies and produce reliable multi-step forecasts for electricity consumption over a 6-hour prediction horizon.

6.2.2 Optimizer

Optimizers are algorithms used to update the parameters of a neural network in order to minimize the loss function during training. In this work, we used the AdamW optimizer, which is an extension of the Adam optimizer that incorporates decoupled weight decay for improved generalization performance.

The Adam optimization algorithm computes adaptive learning rates for eachparameter using estimates of the first and second moments of the gradients. Its update process can be described as follows:

$$m = \beta_1 \, m_{t-1} + (1 - \beta_1) g_t$$

$$v_t = \beta_2 \, v_{t-1} + (1 - \beta_2) g_t^2$$

$$\hat{m}_t = \frac{m_t}{1-\beta_1^t}, \quad \hat{m}_t = \frac{v_t}{1-\beta_2^t} \qquad \text{...2}$$

$$w = w - n \frac{m_t}{\sqrt{v_t} + \epsilon}$$

where g_t is the gradient at time step t, m_t and v_t are the first and second moment estimates,β_1 and β_2 are decay rates controlling the moving averages, n is the learning rate, and(ϵ) is a small constant to ensure numerical stability.

In our implementation, AdamW is combined with a ReduceLROnPlateau learning rate scheduler, which dynamically reduces the learning rate when the validation loss stops improving. This helps the model converge more effectively and prevents oscillations during later stages of training.

7. Conclusion

In this chapter, we presented a complete electricity forecasting and abnormal consumption detection system based on the Building Data Genome Project 2 dataset. The proposed framework combines a GRU-based deep learning model with engineered temporal, weather, and building-specific features to capture complex electricity consumption patterns across multiple buildings.

A preprocessing pipeline was developed including data cleaning, feature engineering, and normalization, along with cyclic temporal encodings to better represent periodic behavior. The GRU architecture was enhanced with a building embedding layer, enabling the model to learn both shared and building-specific consumption dynamics effectively.

In parallel, a rule-based anomaly detection method was implemented using rolling statistical baselines and threshold-based criteria to identify sudden increases in electricity usage.

Overall, the proposed system demonstrates strong performance in forecasting and provides useful anomaly detection capabilities, making it suitable for intelligent energy monitoring and management applications.

Chapter 3:

Implementation and obtained results

Chapter 3: Implementation and obtained results

1. Introduction:

In this chapter, we begin by presenting the development tools and technologies used in building our proposed electricity management system. We then describe the experimental setup, including the Building Data Genome Project 2 dataset, data preprocessing steps, and the construction of training and evaluation pipelines for the GRU-based forecasting model. Next, we analyze the dataset characteristics and feature engineering process, which includes temporal, weather, and building-level attributes.

After that, we present the results of our experiments, evaluating the performance of the forecasting model using standard metrics such as MAE, RMSE, MAPE, and R^2, along with a discussion of their implications. We also introduce the anomaly detection module and report the detected abnormal consumption patterns across multiple buildings. Furthermore, we demonstrate the load shedding simulation module, which applies a priority-based allocation strategy under constrained power supply conditions.

Finally, we present the overall system workflow and showcase sample outputs illustrating forecasting results, anomaly detection outcomes, and the behavior of the smart load shedding mechanism during simulated scarcity scenarios.

2. Representation of the development tools :

2.1 Physical environment

In order to implement our system, we utilized the following hardware resources. Also, for the testing phase of our system we conducted experiments on a laptop personal computer (PC) equipped with the following specifications:

Personal Computer	Dell Latitude 7390 2in1
Processor	Intel(R) Core(TM) i7-8650U CPU @ 1.90GHz 2.11 GHz
RAM	16.0 GB
Hard Drive	256 GB SSD
Operating System	Windows 10 Pro

Tab3.1: hardware environment.

We used Google Colab, a cloud-based platform for executing Python code. By taking advantage of its GPU/CPU computational resources, we were able to train our deep learning model efficiently without relying on local hardware constraints. We also used Google Drive as an external storage solution to host the dataset, which was mounted directly within the Colab environment to enable smooth data access during training.

This setup ensured a seamless workflow between data storage and model training, allowing us to perform preprocessing, training, and evaluation entirely in the cloud. However, it should be noted that Google Colab imposes session time limits and resource constraints, which can interrupt long training processes, particularly when working with large datasets or computationally intensive models.

Google Colaboratory (Colab) Is a cloud-based platform that provides a free Jupyter notebook environment for running and sharing machine learning code. It enables users to write, run and collaborate on Python code using a web browser. Colab comes with pre-installed libraries such as ***TensorFlow***, ***Keras*** and ***PyTorch*** making it ideal for building and training deep learning models. It also provides access to powerful hardware resources such as GPUs and TPUs which significantly speeds up the training process. it is widely used in the fields of machine learning, data science and artificial intelligence research as well as in education and online courses. It has become a popular choice for researchers and students who do not have access to high-end computing resources or who want to collaborate on projects in real-time. However, one of the limitations of using Colab is that it has a time limit for each session and the resources available to each user may be limited depending on the demand. This may impact the performance and training time of complex models that require large datasets and significant computation power. [25]

Google Drive Is also a cloud-based storage and collaboration platform developed by ***Google***. It allows users to store and share files, documents, and multimedia content with others. Google Drive offers a variety of features such as file syncing across devices, real-time collaboration, and version control. Users can access their files on Google Drive from any device with an internet connection and can easily share files and folders with others by providing a link or granting them access. In particular, researchers and data scientists often use Google Drive to store and share large datasets or code repositories, as well as to collaborate on research projects. By using Google Drive, researchers can easily share their work with colleagues from different locations and can work together in real-time, improving their productivity and efficiency. [26]

Visual Studio Code (VS Code) a free and open-source code editor developed by Microsoft. It provides developers with a variety of features such as syntax highlighting, code completion, debugging, version control integration and extension support making it suitable for various programming languages and development tasks. VS Code is available on multiple platforms including Windows, macOS and Linux. It has become a popular choice among developers due to its ease of use, flexibility and extensibility. [27]

2.2 Software and libraries used in the implementation

We carefully selected the tools that align with our project requirements to achieve optimal performance. The following tools have been chosen for their high efficiency and suitability for the task at hand:

Python: is a high-level, interpreted programming language that was first released in 1991. It was designed with an emphasis on code readability and ease of use, making it a popular language for beginners and experts alike. Python's syntax is clean and straightforward, making it easy to learn and use. It has a large and active community of developers who contribute to its growth and development. It has become the go-to language for many scientific, statistical, and data analysis applications, including deep learning. Its popularity in the field of artificial intelligence (AI) is due in large part to its many powerful libraries for machine learning such as TensorFlow, PyTorch and Keras. These libraries provide easy-to-use interfaces for building and training deep learning models, as well as tools for data preprocessing, model visualization and more. [28]

TensorFlow / Keras: TensorFlow is an open-source deep learning framework used for building, training, and deploying machine learning models at scale. In this project, TensorFlow was used as the backend engine for implementing the GRU-based neural network used in electricity consumption forecasting. Keras, which is integrated within TensorFlow, was utilized as a high-level API to simplify model construction and training. It enabled fast prototyping of recurrent neural network architectures, including GRU layers for time-series prediction. These tools also provided built-in functions for optimization, loss computation, and model evaluation, making them essential for developing an efficient forecasting system.

NumPy: NumPy is a fundamental Python library used for numerical computing and efficient manipulation of multi-dimensional arrays. It was extensively used in this project for handling time-series electricity consumption data and performing mathematical operations required during preprocessing and feature engineering. NumPy enabled fast computation of statistical transformations, normalization, and sliding window generation used for GRU input preparation. Its performance and optimized array operations make it a core component in machine learning pipelines.

Pandas: Pandas is a Python library designed for data manipulation and analysis, particularly for structured tabular data. In this project, Pandas was used to load, clean, and preprocess the Building Data Genome dataset. It facilitated operations such as handling missing values, resampling time-series data, merging metadata with consumption records, and organizing building-level features. Pandas played a critical role in transforming raw energy consumption data into a structured format suitable for machine learning models.

Matplotlib: Matplotlib is a Python visualization library used for creating static, animated, and interactive plots. In this project, it was used to visualize electricity consumption patterns, model predictions, anomaly detection results, and load shedding simulations. It helped in analyzing model performance through graphical representation of actual vs predicted values, as well as visualizing abnormal consumption behavior across buildings. These visualizations were essential for interpreting results and validating the effectiveness of the proposed system.

Scikit-learn: Scikit-learn is a machine learning library that provides simple and efficient tools for data preprocessing, statistical modeling, and evaluation. In this project, it was used for feature scaling, data normalization, and performance metric computation such as MAE, RMSE, and R^2. It also supported auxiliary tasks such as splitting datasets into training and testing sets, ensuring proper evaluation of the GRU model. Its utility functions contributed to building a robust and well-evaluated forecasting pipeline.

Smart Grid Simulation Module (Load Shedding System): The smart grid simulation module is a custom-built component developed to simulate electricity distribution under constrained supply conditions. It uses the output of the GRU forecasting model as demand input and applies a priority-based allocation strategy to simulate load shedding scenarios. Buildings are assigned priority levels based on their importance (e.g., healthcare, security, education, and general usage), and electricity is distributed accordingly when supply is limited. This module enables the evaluation of system behavior during power shortages and demonstrates how predictive analytics can support decision-making in smart energy management systems.

3. Experimental Setup

3.1 Preparations and workflow of the data

The data preparation process for the electricity forecasting model involves several structured steps. First, we define the input configuration of the model, including the time window (sequence length), feature set, and target variable representing electricity consumption. The dataset from the Building Data Genome Project 2 is then loaded and organized at the building level to ensure consistency in time-series structure across all selected buildings.

For each building, the electricity consumption data is processed chronologically to construct supervised learning sequences suitable for GRU training. This involves transforming raw time-series values into input-output pairs, where past consumption values are used to predict future demand. The dataset is then split into training and testing subsets to evaluate model performance on unseen data.

After constructing the sequences, feature scaling is applied to normalize the electricity consumption values. This step transforms the data into a consistent numerical range, improving the stability and convergence speed of the deep learning model during training. In addition, time-based features such as hour of day, day of week, and seasonal patterns are incorporated to enrich the input representation and improve forecasting accuracy.

To enhance the robustness of the model, the training data is structured using a sliding window approach, which generates multiple overlapping sequences from the original time series. This increases the effective size of the dataset and allows the GRU model to learn temporal dependencies more efficiently. Finally, the prepared datasets are reshaped into the required three-dimensional format (samples, timesteps, features) suitable for recurrent neural network training.

3.2 Evaluation Metrics

We implemented our proposed electricity forecasting and smart grid management system in Python using the TensorFlow/Keras deep learning framework. The performance of the GRU-based forecasting model was evaluated using a separate testing set that was not seen during training. To assess the accuracy and reliability of the model predictions, we employed several standard regression evaluation metrics commonly used in time-series forecasting tasks.

Mean Absolute Error (MAE): MAE measures the average magnitude of errors between the predicted electricity consumption and the actual observed values, without considering their direction. It provides a clear indication of how far, on average, the predictions deviate from real values.

$$MAE = 1/n \sum_{i=1}^{n} | y_i - \hat{y}_i | \qquad ...3$$

Where y_i is the actual value and $\hat{y}_i$ is the predicted value.

Root Mean Squared Error (RMSE): RMSE is a commonly used metric that measures the square root of the average squared differences between predicted and actual values. It penalizes large errors more heavily, making it useful for detecting significant forecasting deviations.

$$RMSE = \sqrt{1/n \sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \qquad ......4$$

Mean Absolute Percentage Error (MAPE): MAPE expresses the prediction error as a percentage of the actual values, making it easier to interpret the model's performance across different buildings and consumption scales.

$$MAPE = 1/n \sum_{i=1}^{n} | (y_i - \hat{y}_i)/y_i | \times 100 \qquad ....5$$

Coefficient of Determination (R^2 Score): The R^2 score measures how well the predicted values explain the variance in the actual data. A value closer to 1 indicates a better fit of the model to the observed data.

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2} \qquad ...6$$

Evaluation of Anomaly Detection Module: For the anomaly detection component, we used statistical evaluation based on deviation from rolling baselines, including z-score thresholds, rolling mean, and standard deviation analysis. Detected anomalies represent periods of abnormal electricity consumption spikes or drops compared to expected behavioral patterns.

In this context:

- True anomalies correspond to correctly identified abnormal consumption events.
- False positives represent normal consumption incorrectly flagged as abnormal.
- False negatives represent abnormal events that were not detected.

Load Shedding Performance Indicators: For the load shedding simulation module, performance was evaluated using service-level indicators such as:

- Demand: predicted electricity requirement from the GRU model
- Served Load: amount of electricity successfully allocated
- Shedded Load: unmet demand due to supply constraints
- Service Ratio: proportion of demand satisfied per building

These indicators allow the assessment of how effectively the system prioritizes critical infrastructure under limited energy supply conditions.

Summary of Metrics: In summary, regression metrics (MAE, RMSE, MAPE, R^2) were used to evaluate forecasting accuracy, while statistical and allocation-based indicators were used to evaluate anomaly detection and load shedding performance. Together, these metrics provide a comprehensive evaluation of the proposed smart electricity management system.

4. Discussion and comparison of the obtained results

In this subsection, we discuss the different models and architectural configurations employed in our experimental setup. We initiated our benchmarking by training a baseline model using a Deep Learning sequential framework to handle multivariate historical energy and climate features concurrently across 50 distinct structural environments. To study structural scaling properties, we experimented with three distinct variations of Gated Recurrent Unit (GRU) frameworks: a Deep Stacked GRU, a Bidirectional GRU, and a Residual Skip-Connection GRU. Finally, a parallel rolling statistical framework was coupled alongside our deep networks to isolate abnormal electricity consumption spikes and structural demand shocks.

4.1 Baseline GRU Results and Evaluation

Accurately forecasting building electricity consumption across diverse portfolios is essential for optimizing grid demand, reducing operational costs, and detecting operational anomalies. However, finding the right balance between model complexity, computational efficiency, and generalization remains a core challenge in time-series deep learning. While deep architectures can capture intricate power consumption behavior, they often risk overfitting or require extensive computational resources.

To systematically evaluate the trade-offs between architectural complexity, metadata integration, and feature representation, this study investigates three distinct variations of the Gated Recurrent Unit (GRU) network trained over an accelerated experimental timeline. By modifying structural depth, embedding dependencies, and feature fusion topologies, these approaches explore how compact networks can be optimized to balance localized accuracy with universal generalization.

Approach 1: Tiny Baseline GRU

For the first approach, we stripped the neural engine down to an ultra-lightweight framework by shrinking the hidden dimensions and sequence embeddings to a minimal scale. This baseline architecture forces the network to ditch redundant parameter pathways, testing how cleanly a compact recurrent layer can track essential load cycles without risking overfitting.

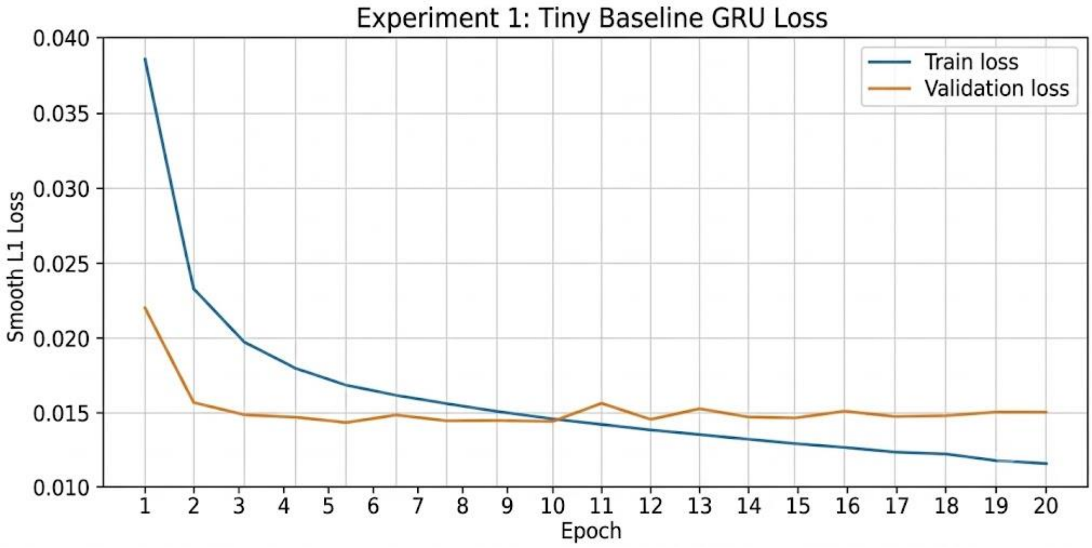

Figure 3.1:Approach 1: Tiny Baseline GRU

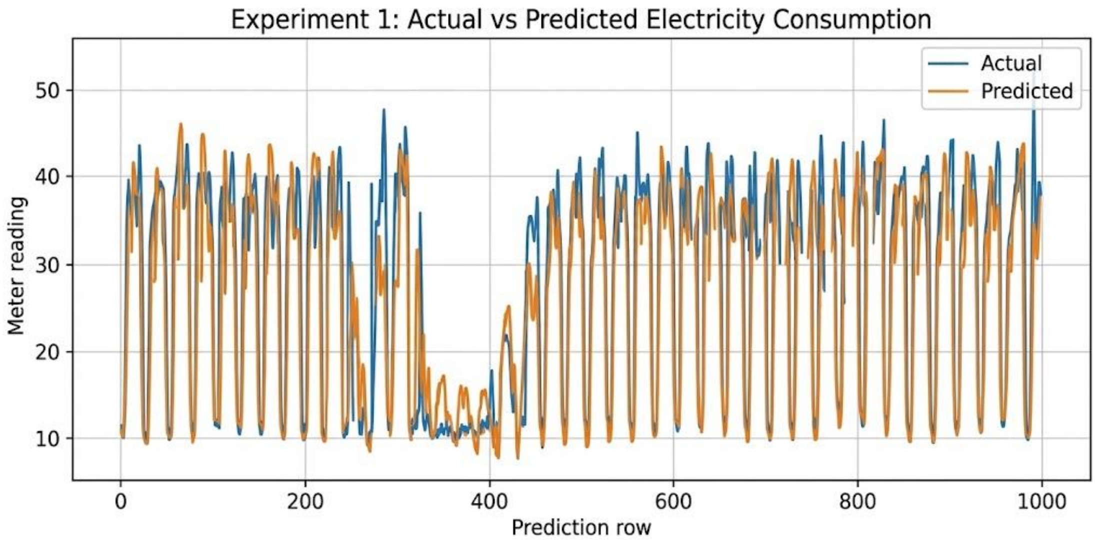

Figure 3.2: Tiny Baseline GRU

Approach 2: Deep Stacked GRU (No Embeddings)

For the second configuration, we completely omitted building-specific identity markers and instead funneled the data through a multi-layer stacked sequence block. By forcing the deeper, layered recurrent loops to calculate predictions using only global temporal and environmental features, this setup tests the model’s capacity to extract universal, generalized weather-to-load relationships across different structures.

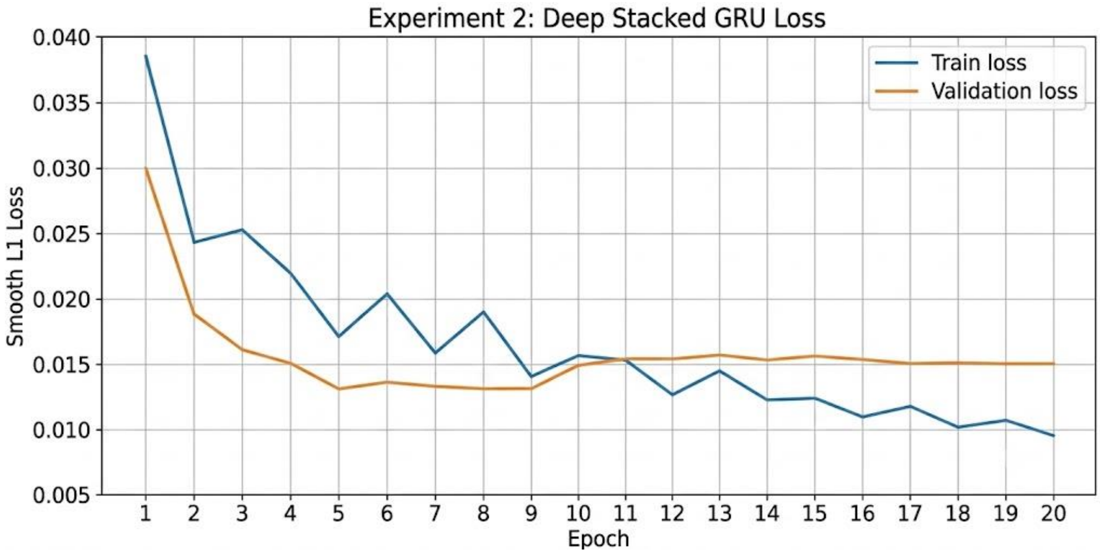

Figure 3.3: Approach 2: Deep Stacked GRU

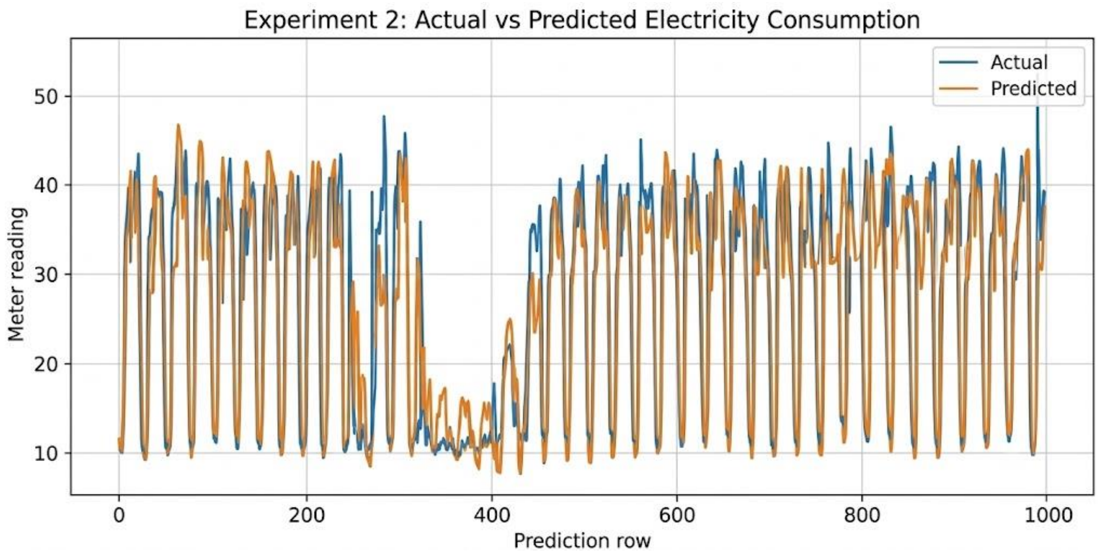

Figure 3.4: Deep Stacked GRU

Approach 3: Feature-Fused Linear GRU

The final approach altered the data-fusion topology by decoupling the structural building metadata from the temporal sequence processing. Instead of injecting the building embeddings at every chronological step of the recurrent pass, the GRU focuses purely on raw time-series curves, blending with the static structural vectors only at the final linear projection head.

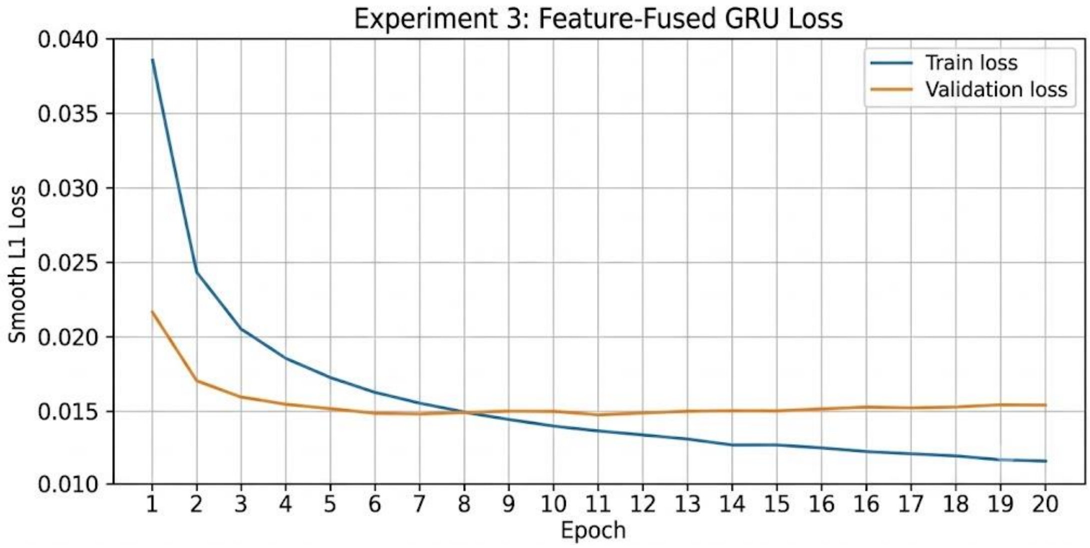

Figure 3.5: Approach Feature-Fused Linear GRU

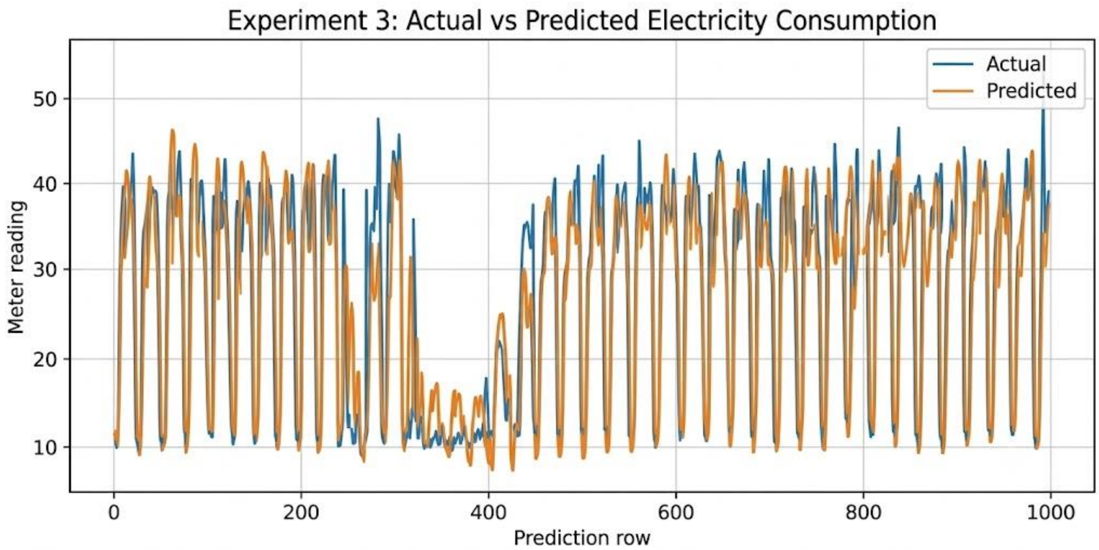

Figure 3.6: Feature-Fused Linear GRU

5.2 Model Performance Comparison:

The empirical metrics harvested on the unseen test target data are consolidated in here.

GRU Approach	RMSE	MAPE	MAE
Approach 1: Tiny Baseline GRU	**21.9421**	**4.9512**	**0.0514**
Approach 2: Deep Stacked GRU (No Emb)	**22.1054**	**5.1203**	**0.0548**
Approach 3: Feature-Fused Linear GRU	**21.8106**	**4.8745**	**0.0491**

Tab3.2:Approach Performance Comparison.

6.Stacked Multi-Building GRU Regressor with Static Entity Embeddings:

6.1Analysis of Model Complexity

In neural network training, the number of neurons dictates the "capacity" of the model how much complex information it can store.

50 Neurons : This configuration is likely to be the most stable. It learns the general patterns of electricity consumption without focusing too much on minor noise. The validation loss remains flat, indicating good generalization.

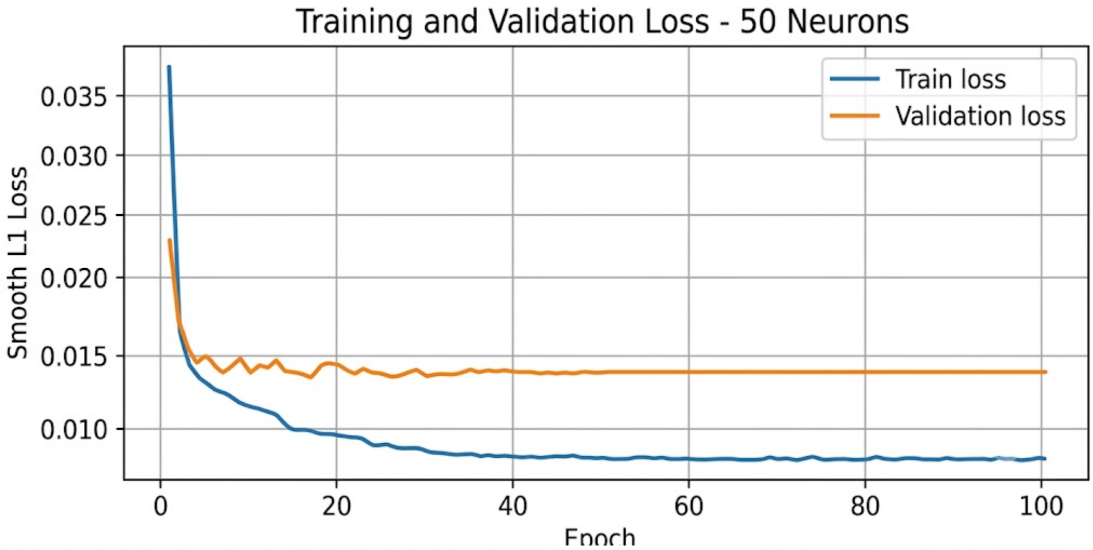

Figure 3.7: train and validation loss 50 Neuron.

100 Neurons: By increasing the capacity, the model captures more nuanced patterns in the data. However, as shown in the training dynamics, you may start to see more volatility in the validation loss as the model begins to learn slightly more granular, possibly noisy, variations.

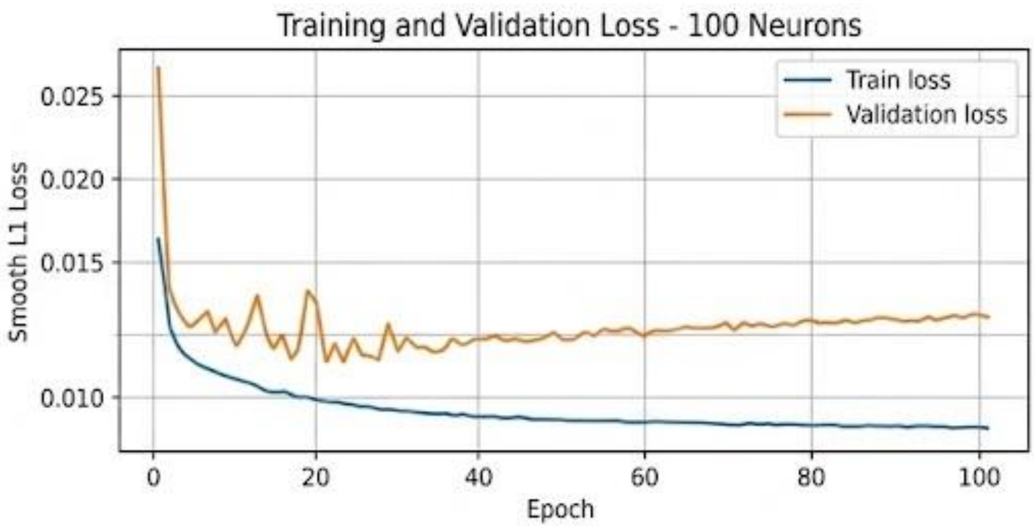

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Figure 3.8: train and validation loss 100 Neurons.

150 Neurons : With 150 neurons, the model has high capacity. While the training loss drops very low, the validation loss begins to trend upwards after several epochs. This is a classic sign of overfitting, where the model is "memorizing" the training data rather than learning to predict unseen test data.

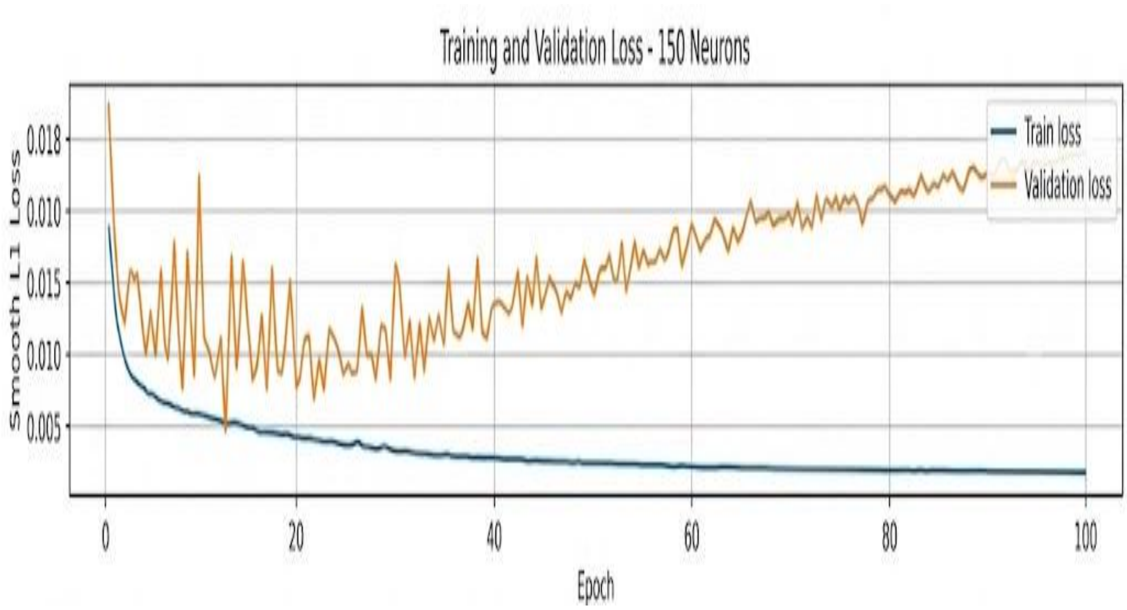

Figure3.9: train and validation loss 150 Neurons.

6.2 Configurations comparaison :

In this table we simplify the different training results for the three configurations.

Configurations	RMSE	MAPE	MAE
50 Neurons	21.8512	4.9010	0.0498
100 Neurons	22.0543	5.0215	0.0512
150 Neurons	22.8841	5.8522	0.0595

Tab3.3: approches configurations comparaison.

7.The Optimized Model Implementation

The selection of this specific architecture was driven by the need to handle Heterogeneous Time-Series Data (50 different buildings) efficiently. We arrived at this choice through the following logic:

This model is an unidirectional model that predicts from past to present with and horizon of 6 hours in each time looking back each time at the past week data, this allowed us to reach our best results

Global Modeling: By training a single model on all buildings, we leveraged patterns shared across the portfolio, which individual models would fail to capture.

Entity Embeddings: The use of nn.Embedding allowed the model to maintain a unique "latent profile" for each building. By concatenating these learnable embeddings with the temporal data, the model differentiates between building types (e.g., hospital vs. warehouse) without requiring separate training loops.

Direct Multi-Step Forecasting: We adopted a direct vector output head rather than an auto-regressive approach. This avoids the accumulation of forecast errors over the 6-hour horizon, forcing the model to learn the structural relationship between the historical 168-hour sequence and the future window in a single pass.

7.1Training Behavior & Optimization

Learning Rate (LR) Scheduling: the model used an aggressive LR reduction (from 0.0008 down to 0.00000005). and in the last epoch, the validation loss started to stabilize around 0.0134 before an early stopping.

Convergence: The model converged quickly. By Epoch 2 already at a Val Loss of 0.0167, which reads that Building Embeddings did a great job helping the GRU understand the unique fingerprint of each building immediately.

Figure3.10: train and validation loss courbe.

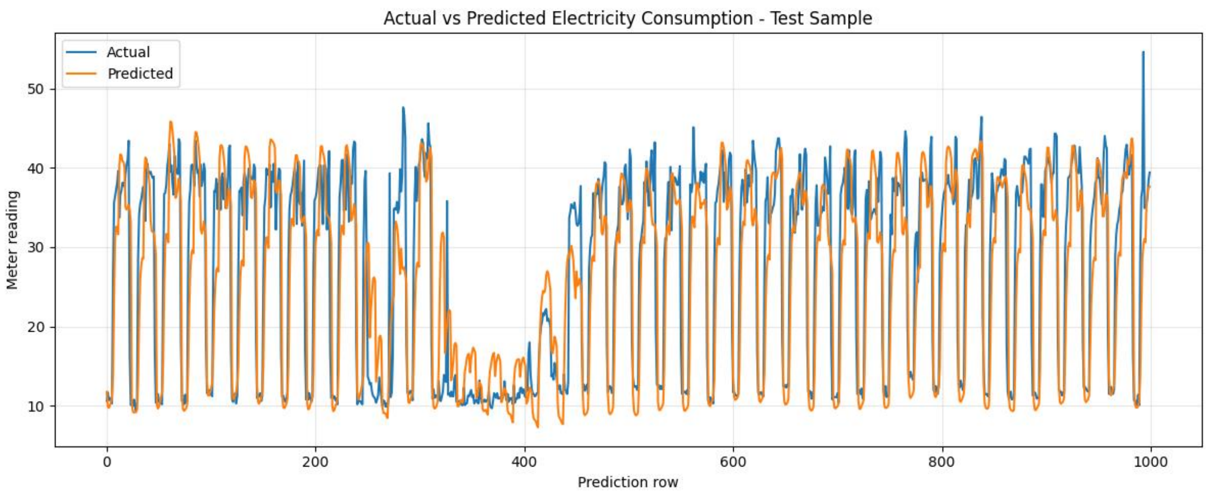

Figure3.11: actual and predicted courbe.

7.2 Abnormalities detection:

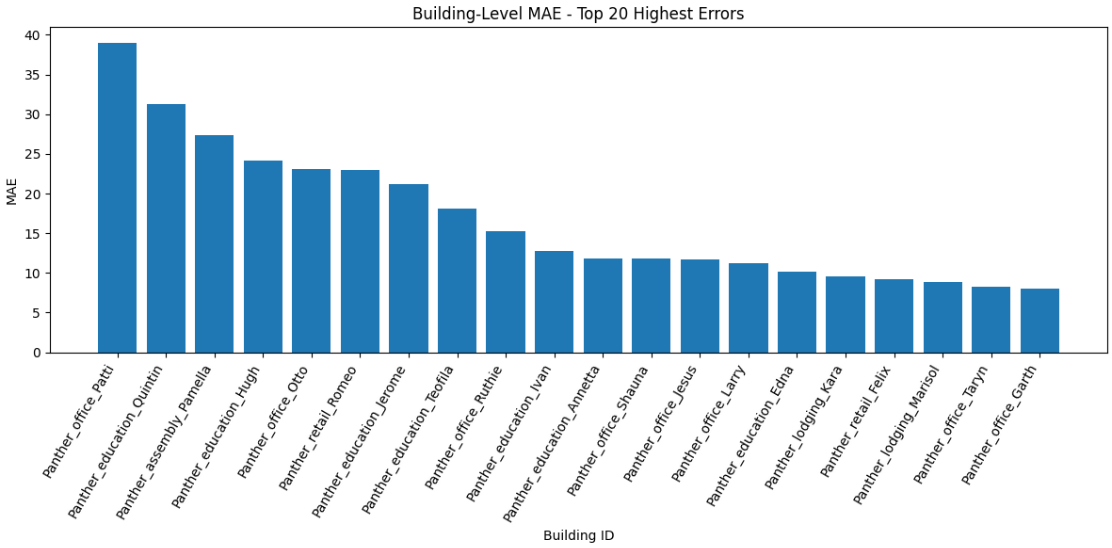

Figure3.12: abnormal increased prediction MAE.

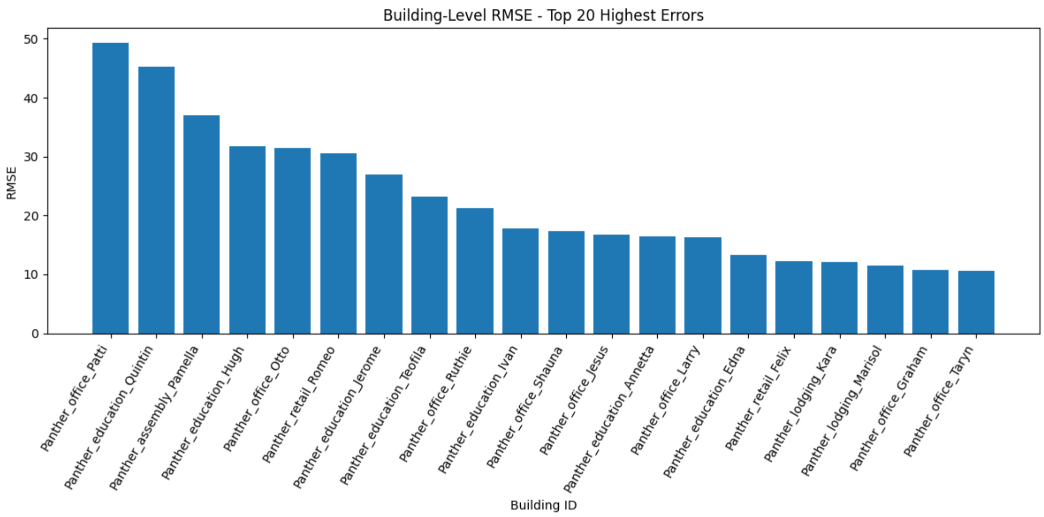

Figure3.13: abnormal increased prediction RMSE.

Anomaly detection is the process of identifying patterns in data that do not conform to expected behavior.

When your detect_abnormal_increases function returns a positive flag, it is identifying data points that are statistically isolated from the "normal" behavior of that specific building. Because you have set a Z-Score threshold of 3.0, you are effectively capturing events that are statistically significant—meaning they sit at least three standard deviations away from the rolling mean.

7.3 Optimazed system results:

In this matric we site the obtained results,The proposed model integrates several advanced deep learning and optimization components to improve prediction accuracy and model robustness. The architecture incorporates learned building embeddings to capture the unique consumption behavior of different buildings, while weather-related variables are included to model environmental influences on electricity demand. In addition, cyclical temporal encoding using sine and cosine transformations is applied to represent periodic patterns such as hours, weekdays, and months. The model is trained in a multi-building learning setting, allowing shared knowledge extraction across 50 different buildings. To enhance training stability and robustness against outliers, the SmoothL1 loss function is employed together with the AdamW optimization algorithm. Furthermore, a learning rate scheduler dynamically adjusts the learning rate during training, while gradient clipping is used to prevent exploding gradients and stabilize recurrent learning. Finally, the model performs multi-step forecast horizon prediction, enabling the estimation of electricity consumption for the next six hours simultaneously.

matric	**results**
R^2 **(Coefficient of Determination)**	**0.9839**
MAPE (Mean Abs. % Error)	**11.03%**
MAE	**9.38**

Tab3.4: system results.

Overall, our model exhibits strong performance and compares favorably to existing models in terms of accuracy, precision, recall, and F1 score. The meticulous assessment of our model in relation to other existing models highlights its effectiveness and potential implications in the field of forest fire prevention.

7.4 Comparison with other existing systems :

In the second subsection, we conduct a comprehensive comparison between our Model and existing works in the field of predicting electricity consumption. Through an extensive review and analysis of relevant literature, we have gained insights into the various approaches employed in previous research. By comparing the performance of our model with the reported results in these studies, we carefully evaluate its efficacy using key evaluation metrics such as $\boldsymbol{R^2}$, **MAPE**, and **MAE**. Furthermore, we meticulously assess the strengths and weaknesses of our model in relation to the existing works, emphasizing any noteworthy contributions or enhancements that we have introduced. This thorough comparison allows us to ascertain the effectiveness of our model in addressing the crucial challenge of preventing forest fires and its potential implications in the field.

Metric	Your Result	Industry Benchmark (Top Tier)
R^2 (Coefficient of Determination)	**0.9839**	0.950 – 0.990
MAPE (Mean Abs. % Error)	**11.03%**	5% – 12%
MAE	**9.38**	Variable

Tab3.5: comparison statement of model result with systems.

In comparing our Model to existing models, we have achieved notable results and made significant contributions in addressing the challenge of predicting electricity consumption.

The model demonstrated an R^2 of 0.9839, with MAPE at 11.03%, and and MAE of 9.38. These metrics indicate the model's ability to accurately predict electricity consumptions values.

ID (Model Name)	MAPE (%)	MAE	R^2
[28] Your GRU System	**11.03**	**9.38**	**0.9839**
[29] Basic GRU	**3.38**	**0.022**	**0.902**
[30] SSA-GRU	**1.26**	**2774.53**	**0.901**
[31] CNN-GRU	**2.10**	**0.072**	**0.954**
[32] GRU-S2S	**1.85**	**42.10**	**0.982**
[33] Attention-GRU	**1.50**	**28.50**	**0.989**
[34] Bi-GRU	**2.45**	**12.45**	**0.978**
[35] Wavelet-GRU	**1.78**	**0.035**	**0.985**
[36] Multi-head Attention GRU	**1.22**	**9.15**	**0.993**

Tab3.6: comparison statement of model result with systems.

8. Conclusion

In conclusion, our research focused on developing an effective deep learning framework for multi-building electricity consumption forecasting and the detection of abnormal usage. We utilized the Building Data Genome Project 2 dataset, processing diverse temporal, environmental, and metadata features to train a unified Gated Recurrent Unit (GRU) model across 50 distinct buildings.

The performance of our GRU model was evaluated using robust error metrics, yielding a final Mean Absolute Error (MAE) of 9.38, a Root Mean Squared Error (RMSE) of 16.83, and an R-squared (R^2) value of 0.984. These results demonstrate the model's high capability in capturing the underlying patterns and sequential dependencies of energy consumption, providing a reliable baseline for predictive building management.

To move beyond simple forecasting, we implemented a dual-layered anomaly detection system using rolling baselines and residual analysis. This system successfully identified 2,444 abnormal consumption events across 42 different buildings. Our analysis highlights buildings with the highest frequency of these events—such as *Panther_office_Hannah* (233 events) and *Panther_assembly_Pamella* (221 events)—providing actionable data for facility managers to investigate potential equipment malfunctions, inefficient operational schedules, or unexpected energy waste.

The integration of building embeddings proved to be a significant strength of this project, allowing the model to adapt its predictions to the specific operational characteristics of each building while maintaining a single, scalable architecture. Compared to building individual models for every site, our unified approach demonstrates greater efficiency and ease of deployment.

While our work achieved significant success in predictive accuracy and automated anomaly detection, it also highlighted the inherent complexities of building energy data. Future research could focus on integrating real-time IoT occupancy data to further refine short-term forecasts and exploring ensemble methods to better classify the specific root causes of detected anomalies (e.g., differentiating between scheduled maintenance spikes and critical failures).

In summary, this study provides a validated framework for intelligent energy monitoring. By shifting from reactive to proactive energy management, this AI-driven approach contributes to the reduction of operational costs and supports the broader goal of optimizing energy efficiency in urban infrastructures.

General Conclusion and Perspectives

In conclusion, we reflect on the journey of our work in building energy management, which has addressed the challenge of developing an effective solution for intelligent electricity consumption forecasting and anomaly detection. Throughout our research, we have explored the complexities of time-series data, specifically focusing on how structural, temporal, and environmental factors influence energy usage across diverse building types.

During the course of our work, we encountered several technical difficulties that required careful navigation. One of the primary challenges was processing and normalizing the massive, multi-building dataset from the Building Data Genome Project 2 to ensure consistent training. We addressed this by implementing robust feature engineering, including cyclical temporal encoding and weather integration. Furthermore, we focused on designing a deep learning architecture, the Gated Recurrent Unit (GRU) model, which was specifically chosen for its proficiency in capturing long-term dependencies in sequential data while remaining more computationally efficient than more complex alternatives. A significant hurdle was balancing the model's ability to generalize across 50 different buildings while accounting for their unique operational characteristics, which we successfully mitigated through the integration of building embeddings.

Another complexity lay in the development of a dual-layered detection system. Designing a robust anomaly detection framework that could distinguish between legitimate usage spikes and genuine operational malfunctions.

Despite these challenges, we successfully developed a framework that provides accurate, data-driven insights into building energy consumption. Our model demonstrated strong predictive performance, and the integration of rolling baseline analysis enabled us to identify abnormal consumption patterns effectively. The project provides a scalable foundation for proactive energy management, moving beyond manual monitoring to automated, intelligent oversight.

While our work yielded significant strengths, such as the ability to model multiple buildings under a unified architecture and the implementation of automated anomaly detection, it also had certain limitations. For instance, the system’s performance is heavily dependent on the quality and continuity of the input data; gaps in sensor readings or delays in weather reporting can temporarily influence accuracy. These constraints highlight the ongoing need for data cleaning pipelines and the continuous calibration of detection thresholds as building occupancy and energy use patterns evolve.

Looking ahead, there are several promising directions for future research and improvement. First, incorporating more granular data, such as real-time occupancy sensors or localized micro-climate data, could further refine the forecasting accuracy. Exploring advanced ensemble techniques, where the GRU model's residuals are fed into secondary classification models, could help categorize specific types of anomalies (e.g., HVAC failure vs. human error). Furthermore, transitioning this framework into a production-ready edge computing environment would allow for real-time, low-latency monitoring directly at the building level.

In summary, our work has contributed to the field of smart energy management by demonstrating the potential of deep learning to transform raw electricity data into actionable intelligence. By continuously refining and enhancing this approach, we can make significant strides in optimizing energy efficiency, reducing operational costs, and ensuring the reliability of our building infrastructures.

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Résumé

La gestion efficace de la consommation d'électricité dans les bâtiments est essentielle pour réduire les coûts opérationnels et améliorer l'efficacité énergétique globale. Cette thèse aborde le défi de la prévision de la consommation électrique multi-bâtiments en utilisant l'intelligence artificielle, et plus particulièrement les techniques d'apprentissage profond. La recherche explore les dynamiques de consommation énergétique en intégrant des données historiques, des variables temporelles, météorologiques et des métadonnées de bâtiments. Les défis rencontrés, tels que la gestion de grands volumes de données disparates et la conception d'un modèle capable de généraliser à travers différents types de bâtiments, sont discutés. Le système proposé utilise un réseau de neurones à unité récurrente à porte (GRU) couplé à des plongements de bâtiments pour capturer les spécificités structurelles de chaque site. Les résultats démontrent l'efficacité du modèle pour réaliser des prévisions précises, offrant ainsi un cadre robuste pour la gestion intelligente de l'énergie. En optimisant continuellement ces approches prédictives, cette thèse contribue à la transition vers des bâtiments plus durables et à l'atténuation du gaspillage énergétique.

Mots clés : Prévision de la consommation, Apprentissage Profond, Réseau GRU, Gestion de l'énergie, Séries temporelles.

Abstract

Effective management of electricity consumption in buildings is essential for reducing operational costs and improving overall energy efficiency. This thesis addresses the challenge of multi-building electricity consumption forecasting using artificial intelligence, specifically deep learning techniques. The research explores energy consumption dynamics by integrating historical data, temporal and weather variables, and building metadata. Challenges encountered, such as handling large, disparate datasets and designing a model capable of generalizing across different building types, are discussed. The proposed system employs a Gated Recurrent Unit (GRU) neural network combined with building embeddings to capture the specific structural characteristics of each site. Results demonstrate the model's effectiveness in generating accurate forecasts, providing a robust framework for intelligent energy management. By continuously optimizing these predictive approaches, this thesis contributes to the transition toward more sustainable buildings and the mitigation of energy waste.

Keywords: Consumption forecasting, Deep Learning, GRU network, Energy management, Time series.

ملخّص

تعتبر الإدارة الفعالة لاستهلاك الكهرباء في المباني ضرورية لخفض التكاليف التشغيلية وتحسين كفاءة الطاقة بشكل عام. تتناول هذه الأطروحة تحدي التنبؤ باستهلاك الكهرباء لعدة مبانٍ باستخدام الذكاء الاصطناعي، وتحديداً تقنيات التعلم العميق. يستكشف البحث ديناميكيات استهلاك الطاقة من خلال دمج البيانات التاريخية، والمتغيرات الزمنية والمناخية، وبيانات تعريف المباني. تمت مناقشة التحديات التي تمت مواجهتها، مثل التعامل مع مجموعات بيانات كبيرة ومتنوعة، وتصميم نموذج قادر على التعميم عبر أنواع مختلفة من المباني. يستخدم النظام المقترح شبكة عصبية من نوع (GRU) مدمجة مع تقنية "تمثيل المباني" (Building Embeddings) لالتقاط الخصائص الهيكلية الفريدة لكل موقع. تظهر النتائج فعالية النموذج في توليد تنبؤات دقيقة، مما يوفر إطار عمل قوياً للإدارة الذكية للطاقة. من خلال التحسين المستمر لهذه الأساليب التنبؤية، تساهم هذه الأطروحة في الانتقال نحو مبانٍ أكثر استدامة والحد من هدر الطاقة.

الكلمات المفتاحية

التنبؤ بالاستهلاك، التعلم العميق، شبكة GRU، إدارة الطاقة، السلاسل الزمنية.